A COMBINED PCA AND ANN APPROACH FOR PREDICTION OF MULTIPLE RESPONSES IN TURNING OF AISI 1020 STEEL

A dissertation submitted in partial fulfillment of the requirements for the award of the degree of

MASTER OF TECHNOLOGY

In

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Submitted by

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CERTIFICATE

Certified that the dissertation entitled "**A COMBINED PCA AND ANN APPROACH FOR PREDICTION OF MULTIPLE RESPONSES IN TURNING OF AISI 1020 STEEL''** is a bonafide work and submitted by **DILLIP KUMAR MOHANTA (210ME2271)** has been carried out under my supervision in partial fulfillment for the award of Master of Technology in **PRODUCTION ENGINEERING** during the academic year 2010-2012. It is an authentic work and no part of this work has been submitted earlier to any other university/ institute for the award of any degree.

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ABSTRACT

This dissertation presents an optimization approach for multiple responses (surface roughness, flank wear and cutting force) in turning of AISI 1020 steel with coated and uncoated inserts using principal component analysis (PCA). Three controllable factors of the turning process were studied at three levels each viz. cutting velocity, feed and depth of cut. L27 Orthogonal array was used for conducting the experiments. Optimum parameters setting to minimize surface roughness, flank wear and cutting force have been found out using Taguchi's parameter design. Experimental results indicate that optimal factor settings for each response are different. Therefore, all the three responses are converted into a single response index through PCA approach. The process parameters are optimized with consideration of all the performance characteristics simultaneously. The analysis of variance (ANOVA) was used to find out the most influential turning parameters for multiple response problems.

It is found that the cutting velocity has significant effect in producing lower responses followed by feed and depth of cut. Since experimentation takes high amount of efforts, cost and time, it is prudent to propose a simple but valid model to predict the response. Therefore, an artificial neural network (ANN) approach, which works on experience of the modeler and shop floor managers, has been proposed in this work. Neural networks offer a number of advantages, including requiring less formal statistical training, ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithms.

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CHAPTER 1

INTRODUCTION

1.1 TURNING OPERATION

The turning is the one most commonly employed operation in experimental work on metal cutting to produce round shaped parts by a single point cutting tool on lathes. The work material is held in the chuck of a lathe and rotated. The tool is held rigidly in a tool post and

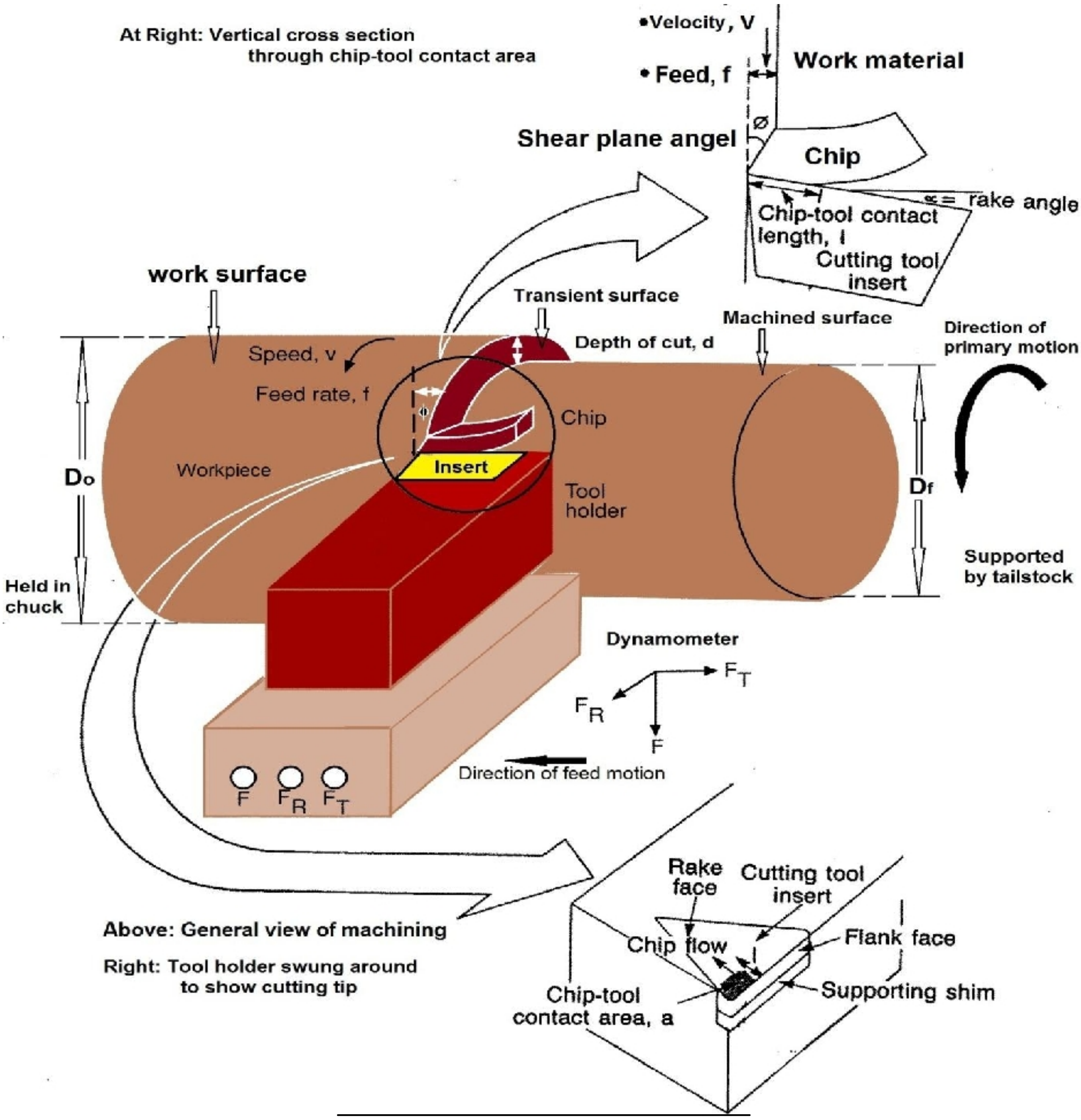


Figure 1.1 Turning operation

fed is given either linearly in the direction parallel or perpendicular to the axis of rotation of the workpiece at a constant rate to cut away a layer of metal to form a cylinder or a surface of more complex profile. The primary motion of cutting is the rotation of the workpiece and the secondary motion of cutting is the feed motion in turning [1]. This is shown diagrammatically in Figure 1.1.

1.1.1 ADJUSTABLE CUTTING FACTORS IN TURNING

Cutting velocity* (V)*: It is the speed at which the metal is removed by the tool from the workpiece. In other words, it is the rate at which the uncut surface of the work passes the cutting edge of the cutting tool. It is usually expressed in m/min.

$$V=\frac{\pi DN}{1000}\ \text{m/min}$$

Where D is the diameter of the workpiece in meter; N is the rotational speed of the workpiece in RPM.

***Feed* (f):** It is the distance moved by the tool in an axial direction at each revolution of the work. It is usually expressed in mm/rev.

***Depth of cut* (d):** It is the thickness of metal removed from the w/p, measured in a radial direction or It is the perpendicular distance measured from the machining surface to the un-machined surface of the w/p or It is the depth of penetration of the tool into the w/p during machining. It is usually expressed in mm.

The turning operation reduces the diameter of the workpiece from the initial diameter D_o to the final diameter D_f. The change in diameter is actually two times depth of cut, d.

$$2d = D_o - D_f$$

TABLE 1.1
Recommended cutting velocities in turning with carbide Inserts

Workpiece Material	**Cutting Velocity**	
	m/min	**ft/min**
Aluminum alloys	200-1000	650-3300
Cast iron, gray	60-900	200-3000
Copper alloys	50-700	160-2300
High-temperature alloys	20-400	65-1300
Steels	50-500	160-1600
Stainless steels	50-300	160-1000
Thermoplastics and thermosets	90-240	300-800
Titanium alloys	10-100	30-330
Tungsten alloys	60-150	200-500

Note: (a) The speeds given in this table are for carbides and ceramic cutting tools. Speeds for high-speed-steel tools are lower than indicated. The higher ranges are for coated carbides and cermets. Speeds for diamond tools are significantly higher than any of the values indicated in the table.

(b) Depths of cut, d, are generally in the range of 0.5-12 mm (0.02-0.5 in.).

(c) Feeds, f, are generally in the range of 0.15-1 mm/rev (0.006-0.040 in./rev).

1.2 GEOMETRY AND NOMENCLATURE CUTTING TOOLS FOR LATHES

Shank: The long, rectangular section of the tool holder that is clamped into the chuck.

Flank: A flat surface of a single-point tool that is adjacent to the face of the tool. During turning, the side flank faces the direction that the tool is fed into the work piece, and the end flank passes over the newly machined surface.

Rake or Face: The flat surface of a single point tool through which, the work piece rotates during turning operation. On a typical turning setup, the face of the tool is positioned upwards.

Back rake angle: If viewed from the side facing the end of the work piece, it is the angle formed by the face of the tool and a line parallel to the floor. A positive back rake angle tilts the tool face back and a negative angle tilts it forward and up. Its value usually varies between 0° and 15°, whereas the back rake angle is usually taken as 0°.

Side rake angle: If viewed behind the tool down the length of the tool holder, it is the angle formed by the face of the tool and the centerline of the work piece. A positive side rake angle tilts the tool face down toward the floor, and a negative angle tilts the face up and toward the workpiece. Its value usually varies between 0° and 15°.

Side cutting edge angle: If viewed from above looking down on the cutting tool, it is the angle formed by the side flank of the tool and a line perpendicular to the work piece centerline. A positive side cutting edge angle moves the side flank into the cut, and a negative angle moves the side flank out of the cut.

End cutting edge angle: If viewed from above looking down on the cutting tool, it is the angle formed by the end flank of the tool and a line parallel to the work piece centerline. Increasing the end cutting edge angle tilts the far end of the cutting edge away from the work piece. Its recommended value ranges from 8° to 15°.

Side relief angle: If viewed behind the tool down the length of the tool holder, it is the angle formed by the side flank of the tool and a vertical line down to the floor. Increasing the side relief angle tilts the side flank away from the work piece.

End relief angle: If viewed from the side facing the end of the work piece, it is the angle formed by the end flank of the tool and a vertical line down to the floor. Increasing the end relief angle tilts the end flank away from the work piece. Hence, clearance angle is a must and must be positive, 30 – 15^0 depending upon tool-work materials.

Nose radius: It is the rounded tip on the cutting edge of a single point tool. A zero degree nose radius creates a sharp point of the cutting tool. Large nose radius will induce chatter.

Lead angle: It is the common name for the side cutting edge angle. If a tool holder is built with dimensions that shift the angle of an insert, the lead angle takes this change into consideration. The back rake angle affects the ability of the tool to shear the work material

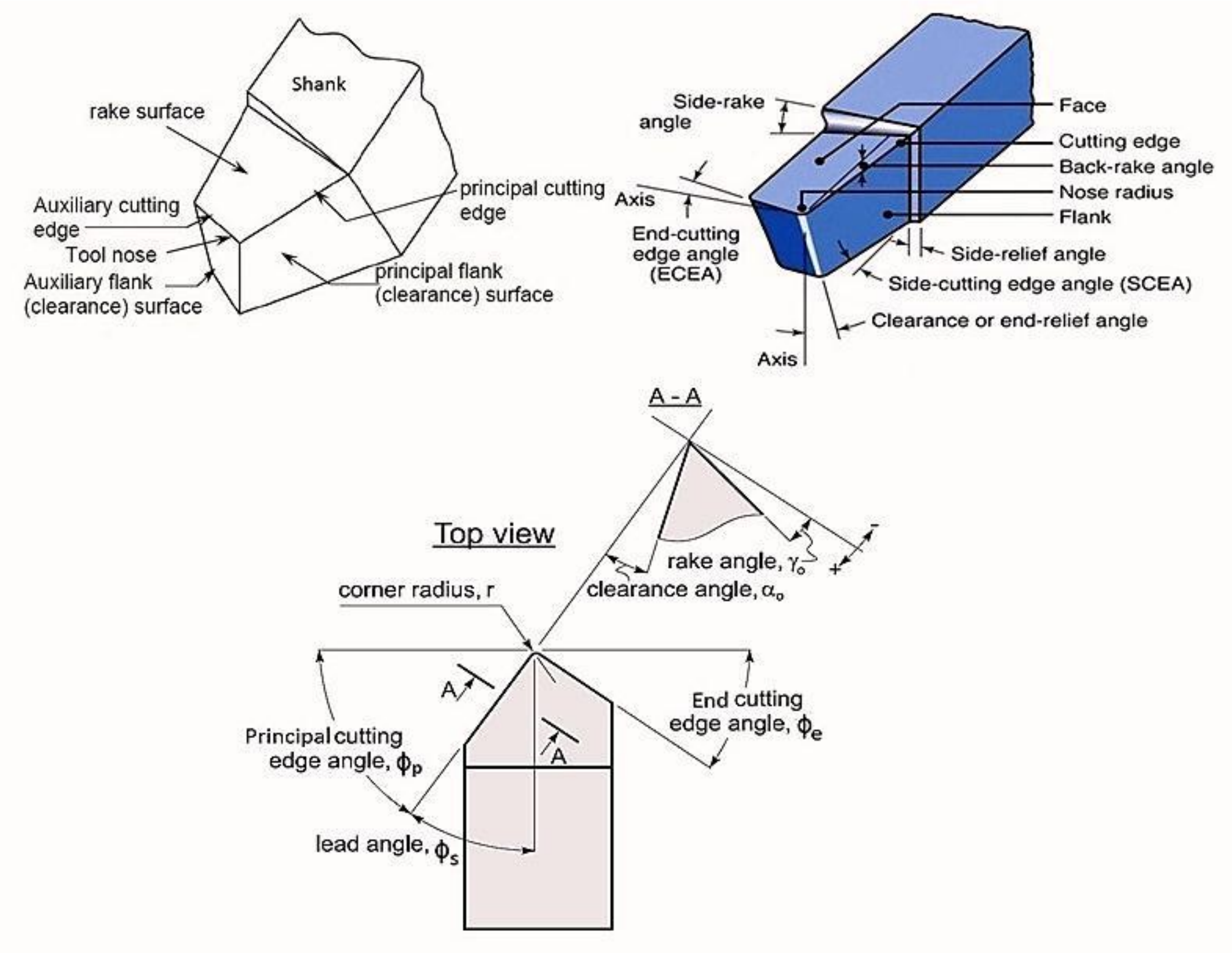


Figure 1.2 Cutting edges, surfaces and angles on the cutting part of a turning tool [2]

and form the chip. It can be positive or negative. Positive rake angles reduce the cutting forces resulting in smaller deflections of the work piece, tool holder, and machine. If the back rake angle is too large, the strength of the tool is reduced as well as its capacity to conduct heat. In machining hard work materials, the back rake angle must be small, even negative for carbide and diamond tools. The higher the hardness, the smaller will be the back rake angle. For high-speed steels, back rake angle is normally chosen in the positive range. Usually, the recommended value for the lead angle should range between 15° and 30°.

1.3 CUTTING TOOL MATERIALS

In today's metalworking industry many types of tool materials, ranging from high carbon steel to ceramics and diamonds, are used as cutting tools. The best tool should be chosen to get the job done quickly, efficiently, and economically.

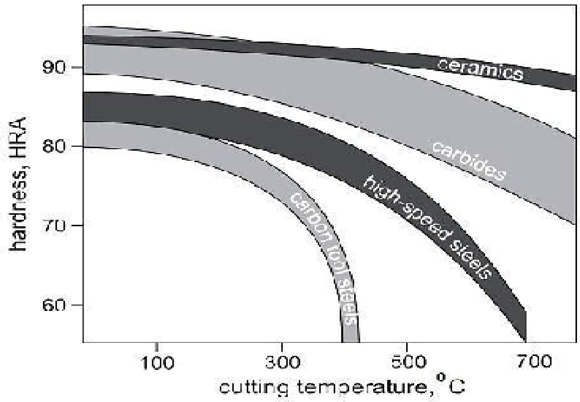


Figure 1.3 Hardness for different tool material

A cutting tool must have the following characteristics in order to produce good quality and economical parts:

Hardness: It is generally the hardness at elevated temperatures (so-called hot hardness) and is the ability to retain that hardness and strength in high cutting temperatures (Fig 1.3).

Toughness: It helps the cutting edge of the insert to absorb the cutting forces and shock loads produced while machining, particularly relevant when intermittent cutting operations occur so that the tool doesn't chip or fracture.

Wear Resistance: The ability of a metal to resist the gradual wearing away caused by abrasion and friction.

***Lack of affinity*:** This condition should be present between the tool and the workpiece. Any degree of affinity will lead to the formation of a built-up edge (BUE).

Thermal Conductivity and Specific Heat: Thermal conductivity is the ability of the material to conduct heat while the specific heat decides about its ability to absorb and contain heat. High values of both these properties are desirable so that the heat generated at the cutting edge is absorbed and conducted away from the cutting edge without increasing its temperature. These properties predominantly influence the amount of chip curl and the chip contact length provided that the temperature dominant cutting speed range is used.

The materials from which cutting tools are made should be characteristically hard and strong. There is a wide range of tool materials available for machining operations and the general classification and use of these materials are given here [3].

Carbon steels: It is the oldest of tool material. Widely used for drills, taps, broaches, hacksaw blades and reamers. The carbon content is 0.6-1.5% with small quantities of silicon, chromium, manganese, and vanadium to refine grain size. Maximum hardness is about HRC 62.This material has low wear resistance and low hot hardness. Carbon steels start to soften at a temperature of about 180^{o}C. This limitation means that such tools are rarely used for metal cutting operations. Plain carbon steel tools, containing about 0.9% carbon and about 1% manganese, hardened to about 62 HRC, are widely used for woodworking. These are unstable very inexpensive and extremely sensitive to heat. Increase in carbon content increases wear

TABLE 1.2
ISO R513-1975(E) ‘‘Application of carbides for machining by chip removal.’’[3]

Group Number	**Carbide Type**	**Work Materials**	**Scheme (Cobalt and Properties)**
P (blue)	Highly alloyed WC–TiC–TaC–Co	Steel, steel castings, ductile cast iron(ferrous metals with long chips)	P01 (low Co for maximum hardness& Maximum speed) to P50 (high Co for maximum toughness& Maximum Feed)
M (yellow)	Alloyed WC–TiC–TaC–Co	Free-cutting steel, gray cast iron, austenitic stainless steel, super-alloys	M10 (low Co for maximum hardness& Maximum speed) to M40 (high Co for maximum toughness& Maximum Feed)
K (red)	Straight WC–Co	Nonferrous metals and alloys, gray castiron (ferrous metals with shortchips), non-metallics	K01 (low Co for maximum hardness& Maximum speed) to K40 (high Co for maximum toughness& Maximum Feed)

resistance of the tool. Mostly obsolete in today's commercial machining, although it is still commonly found in non-intensive applications. The cutting speed to use for plain carbon tool steel should be approximately one-half of the recommended speed for high-speed steel.

High-speed Steels (HSS): It is the most common cutting tool material used today. The representative metallurgical composition of HSS is 1.9% carbon, 0.3% manganese, 8% tungsten, and 3.8% chromium, with iron the remainder. The M series (10% Mo, with Cr, V, W and Cobalt as alloying elements) represents tool steels of molybdenum type and the T series (18%W, 4% Cr, 1% V and Cobalt as alloying elements) represents those of the tungsten type. HSS tools are tough and suitable for interrupted cutting and are used to manufacture tools of complex shape such as drills, reamers, taps, dies, broaches and gear cutters. Tools may also be coated to improve wear resistance. HSS accounts for the largest tonnage of tool materials currently used. These are unstable, inexpensive and retain hardness at moderate temperatures. Hardness up to 63-65 HRC. They provide sharp cutting edges. Typical cutting speeds range: 10 - 60 m/min.

Cast Cobalt alloys: They have compositions of about 40 - 55% cobalt, 30% chromium and 10 - 20% tungsten and are not heat treatable. Maximum hardness values of 55 - 64 HRC. They have good wear resistance but are not as tough as HSS but can be used at somewhat higher speeds than HSS. These are stable, expensive and not used much.

Carbide: Perhaps the widest utilized cutting tool materials today are the cemented carbide family of which the group from tungsten carbide is most readily employed. The two basic groups of carbides used for machining are Tungsten carbide and Titanium carbide. Tungsten carbide (WC) is a composite material consisting of tungsten-carbide particles bonded together in a cobalt matrix. WC is also called cemented carbide. These tools are made with powder metallurgy techniques. The proportion of cobalt (the usual matrix material) present has a significant effect on the properties of carbide tools. 3 - 6% matrix of cobalt gives greater hardness while 6 - 15% matrix of cobalt gives a greater toughness while decreasing the hardness, wear resistance and strength. WC particles, which are 1-5 μm in size, are then pressed and sintered into the desired insert shapes. So these are also called Sintered carbides. Tungsten carbide tools are commonly used for machining steels, cast irons and abrasive non-ferrous materials. Titanium carbide (TiC) has a higher wear resistance than tungsten but is not as tough. With a nickel-molybdenum alloy as the matrix, TiC is suitable for machining at higher speeds than those which can be used for tungsten carbide. Typical cutting speeds are: 30 - 150 m/min or 100 - 250 when coated. They are Stable & moderately expensive. Hardness up to about HRC 90. Most cemented carbide insert selection guides group insert grades by the materials they are designed to cut. The international standard for over 30 years used for carbide cutting of workpiece materials is: ISO 513-1975E Classification of Carbides (Tab.1.3). These ISO 513 code utilizes 3 broad letter-and-colour classifications. Each grade within a group is assigned a number to represent its position from maximum hardness to maximum toughness (higher the number, tougher the tool). A tool surface should be very hard, non-reactive and should provide a barrier to diffusion of tool constituents to work material. At the same time the tool matrix should be sufficiently tough to withstand impact forces arising during interrupted cuts e.g.in milling.

Ceramics: Ceramic materials are composed primarily of fine-grained, highly pure aluminum oxide (Al_2O_3), pressed and sintered with no binder at high temperature. Two types are available: white, or cold-pressed ceramics, which consists of only Al_2O_3 cold pressed into inserts and sintered at high temperature. Black, or hot-pressed ceramics, commonly known as cermets (from ceramics and metal).This material consists of 70% $Al_2O_3$and 30% TiC.

Both materials have very high wear resistance but low toughness. Therefore they are suitable only for continuous operations such as finishing turning of cast iron and steel at very high speeds. There is no occurrence of built-up edge, and coolants are not required. Use of cemented carbide tools is quite popular in industries; however, such tools are expensive since they contain comparatively elements such as W, T (titanium), tantalum and cobalt. The ceramic tool materials, also known as cemented oxides are available in the form of tips. Ceramic tips are considerably cheaper than those of cemented carbides. Their hardness ranges from89 to 95 HRC. Ceramics are wear as well as heat resistant (upto about 1200°C).This enables them to machine materials at very high cutting speed (≈ 3700 m/min in finish turning of C.I.). The main limitation is their brittleness (bending strength up to 45 kgf/mm^2). Ceramic tool materials yield higher production rate as compared to carbide tools. The cermet which contains besides aluminium oxide, metal additions (tungsten, molybdenum, boron, titanium, etc.) in an amount upto10 percent. These additions reduce the brittleness of ceramics to some extent, but this also reduces their wear resistance. Ceramic + Metals → Cermet. Sharp cutting edges and positive rake angles are to be avoided.

Cubic boron nitride (CBN): Next to diamond, CBN is the hardest tool material and it is also the second most fragile. CBN is used mainly as coating material because it is very brittle. In spite of diamond, CBN is suitable for cutting ferrous materials. It is stable and expensive. It offers extremely high resistance to abrasion at the expense of much toughness. It is generally used in a machining process called "hard machining", which involves running the tool or the part fast enough to melt it before it touches the edge, softening it considerably. Used almost exclusively on turning tool bits. The hardness is higher than 95 HRC. Sharp edges generally not recommended.

Diamond: Diamonds are the hardest of all the materials and have low chemical activity, low value of coefficient of friction, and a slight tendency for adhesion to metals. But, they are almost unaffected by acids and alkalis. Their wear resistance and heat resistance (1500°C) is very high. This cutting tool material is stable, brittle and very costly. Superior resistance to abrasion but also high chemical affinity to iron which results in being unsuitable for steel machining. It is used where abrasive materials would wear anything else. It is extremely fragile. Used almost exclusively on turning tool bits although it can be used as a coating on many kinds of tools. Sharp edges generally not recommended. Synthetic diamonds are obtained from ordinary graphite by subjecting it to extremely high pressure and temperature. Diamond powder (crushed crystals) is used for polishing precious stones, making diamond abrasive tools (wheels, disks, sticks, files, honing stones, lapping stones), etc. Single point diamond tool bits has been used for finishing operation in machining of non-ferrous metals and alloys, and non-metallic materials. The recommended size of diamonds that are to be secured by some means in a holder, is one carat (= 0.2 gm). Diamonds are also used to true and dress ordinary grinding wheels and diamond wheels.

TABLE 1.3
General operating characteristics of cutting tool materials

Tool materials	**General characteristics**	**Models of tool Wear or failure**	**Limitations**
High-speed steels	High toughness, resistance, wide range of roughing & finishing cuts.	Flank wear, crater wear.	Low hot hardness, limited hardenability and limited wear resistance.
Uncoated carbides	High hardness over A wide range of temperatures, wear resistance, wide range of applications.	Flank wear, crater wear.	Cannot use at low Speed because of Cold welding of Chips and microchipping.
Coated carbides	Better wear resistance over uncoated carbides, better frictional and thermal properties.	Flank wear, crater wear.	Cannot use at low Speed because of Cold welding of Chips and microchipping.
Ceramics	High hardness at elevated temperatures, high abrasive wear resistance.	Depth of cut line notching, microchipping, gross fracture.	Low strength, low thermo-mechanical fatigue strength.
Cubic boron nitride (CBN)	High hot hardness, toughness, cutting edge strength.	Depth of cut line notching, chipping, oxidation, graphitization.	Low strength, low chemical stability at higher temperature.
Diamond	High hardness and toughness, high abrasive wear resistance.	Chipping, oxidation, graphitization.	Low strength, low chemical stability at higher temperature.

1.4 TOOL COATINGS

Coatings of single layer or multiple layers of different thickness [4] are done on the surface of a tool insert to improve its properties depending on the applied requirements and procedures. The most common requirements that are set in the application of certain metal objects are: wear resistance, corrosion protection, resistance to high working temperature, low coefficient of friction and reduction of machined material adhesion to the workpiece.

Depending on the material and conditions of its use, the process of coating is elected, and because of expressive advantages related to the other, usually in the application are given below.

<table>
<tr><td colspan="7">TABLE 1.4
General characteristics of cutting tool materials</td></tr>
<tr><td></td><td>High-speed steel</td><td>Uncoated carbides</td><td>Coated carbides</td><td>Ceramics</td><td>Cubic boron nitride</td><td>Diamond</td></tr>
<tr><td>Hot hardness</td><td colspan="6">→</td></tr>
<tr><td>Toughness</td><td colspan="6">←</td></tr>
<tr><td>Impact strength</td><td colspan="6">←</td></tr>
<tr><td>Wear resistance</td><td colspan="6">→</td></tr>
<tr><td>Chipping Resistance</td><td colspan="6">←</td></tr>
<tr><td>Cutting speed</td><td colspan="6">→</td></tr>
<tr><td>Thermal shock resistane</td><td colspan="6">←</td></tr>
<tr><td>Tool material cost</td><td colspan="6">→</td></tr>
<tr><td>Depth of cut</td><td>Light to heavy</td><td>Light to heavy</td><td>Light to heavy</td><td>Light to heavy</td><td>Light to heavy</td><td>Very light</td></tr>
</table>

CVD - chemical vapor deposition

In this process, hard layer occurs by gas reaction on the surface of objects that are coated at relatively high temperatures (about 1000^0C). Movement of particles in the working chamber is not directed to form a smooth layer without taking the necessary measures (e.g., movement of pieces). By this method, elements of a very complex shape can be coated (area outside the zone of sight). Secondary products arise during chemical reaction that need to be removed from the chamber and are very harmful to the environment. Hard metal parts are usually

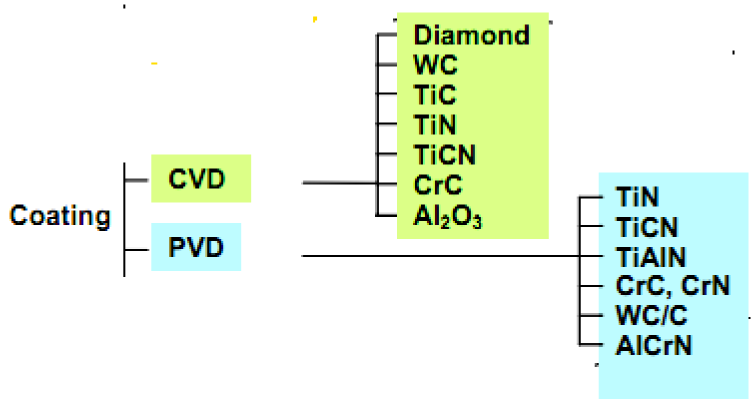


Figure 1.4 Coating processes

coated by this procedure. If this process is applied to steel parts, then they must be subsequently thermally processed.

PVD - physical vapor deposition

Layers of pure metal (aluminum, chromium, titanium, etc.) can be created by this process, layers of compounds (carbide of titanium, tantalum, molybdenum, etc.) on the surface of metal parts. Parts must be electro conductive and unmagnified. The first of all, material to be deposited has to be put on to the steam phase by evaporation in a vacuum. Then the particles of evaporated material are directed by electric field to the negatively charged surface of the working objects. The procedure is performed at relatively low temperatures of 200 to 500^0 C, and the thickness of deposited layer is several microns. In order to enable layer thickness to be equal, parts must be globally rotated in chamber work space, and parts that have areas outside the zone of sight can't be high quality coated (maximum depth of the coating of the hole is up to diameter of the hole). Low temperature of process enables the deposition of layers on the finished parts and requires no additional heat or finishing (grinding, polishing). This equipment is very expensive because it requires sophisticated reactor and vacuum system to create the conditions for transportation and generating of steam species. But it is environmentally acceptable, because of the low process temperatures and non-separation of harmful ingredients.

What is the difference between PVD and CVD?

• In PVD, the material that is introduced onto the substrate is introduced in solid form whereas, in CVD, it is introduced in a gaseous form.

• In PVD, atoms are moving and depositing on the substrate, but in CVD, the gaseous molecules will react with the substrate.

• The deposition temperatures of PVD and CVD are different. PVD coating is deposited at a relatively low temperature (around 250°C~450°C) than CVD.(CVD uses high temperatures in the range of 450 ^{0}C to 1050 ^{o}C).

• PVD is suitable for coating tools that are used in applications that demand a tough cutting edge. CVD is mainly used for depositing compound protective coatings.

TiN (Titanium Nitride): It is the most used in cutting and forming of metal and decorative purposes because of its characteristic yellow color. [5]Application of TiN coating on cutting tools extends the life of the tools, because it reduces the coefficient of friction on the surface. It helps the flow of chips, preventing deposits of material on the cutting tool edge, reduces the cutting force and heating of cutting tool. High chemical stability makes TiN suitable for use in food industry and medicine.

- Material: titanium nitride
- Deposition: PVD, CVD
- Color: gold
- Thickness: 1 - 4 µm
- Speed: Low
- Microhardness: 2300 HV
- Deposition temperature: 200 - 450 °C
- Maximum working temperature: 500 °C

Coating properties

• High surface hardness

• Good adhesion to the substrate

• Good chemical stability

• Increased toughness

• Ecologically suitable for use

• Low heat conductivity

TiCN (Titanium Carbo- Nitride): TiCN is specially designed with a complex multi-layer structure, which gives it higher hardness and lower coefficient of friction than TiCN. Besides high hardness, TiCN has a high toughness and resistance to abrasion at high temperatures. These features are desirable for many applications, eg. interrupted cutting, when changed temperatures occur at the cutting edge during operation. It has successful application on milling cutters, reamers, drill bits and cemented carbide inserts. In operations of forming, TiCN reduces wear and problems that result from sticking of material on the tool.

- Material: titanium nitride, carbon
- Deposition: PVD, CVD
- Color: Light gray
- Thickness: 2 - 4 µm
- Speed: Medium
- Microhardness:3500 HV
- Deposition temperature: 200 - 350 °C
- Maximum working temperature: 400 °C

Coating properties

- High hardness
- Good adhesion to the substrate
- Good wear resistance at high temperatures

- Increased toughness
- Low coefficient of friction
- High heat conductivity

ZrCN (Zirconium carbo- nitride): It has excellent erosion resistance, good lubricity and ductility combined with an attractive appearance to make it stand out from the all the rest. This coating has worked well in all non-ferrous applications. Recommended Applications: Aluminum, Brass, Cast Iron, Graphite, Ni Alloys, Ti Alloys, 300/PH Series Stainless Zinc, Glass-filled Plastics (Not recommended for carbon steels). Material: Zirconium, carbon, Nitrogen

- Deposition: CVD
- Color: Light gray
- Thickness: 2 - 5 µm
- Speed: Medium
- Microhardness:2800 HV
- Deposition temperature: 300 - 600°C
- Maximum working temperature: 500 °C

Al_2O_3 (Aluminium oxide): A wear resistant CVD coating that forms an excellent thermal and chemical barrier between the tool and workpiece. Typically used on carbide inserts, aluminum extrusion tooling and resistance welding tips. This coating is used in several of our CVD multi-layer coatings.

- Deposition: CVD
- Color: grey blue
- Thickness:4 - 8 µm
- Speed: High
- Microhardness:3500 HV
- Deposition temperature: 750 - 1000°C

- Maximum working temperature: 1000 °C

Coating properties

- Excellent heat resistance
- Good wear resistance at high temperatures
- Chemical stability
- Lack of affinity
- Durability under low impact conditions

1.5 SURFACE FINISH AND ROUGHNESS

Surface finish of the machined parts is one of the important criteria to judge the success of a machining operation as it is an important quality characteristic that may dominate the functional requirements of many component parts as well as production cost. For example, good surface finish is necessary to prevent premature fatigue failure, creep, to improve corrosion resistance, light reflection, heat transmission, lubrication, electrical conductivity, to reduce friction, wear, noise and finally to improve product life. Therefore, achieving the required surface finish is crucial to the success of machining operations.

Surface roughness is a measurable characteristic based on the roughness deviations. Surface finish is a more subjective term denoting smoothness and general quality of a surface. In popular usage, surface finish is often used as a synonym for surface roughness.

Surface roughness represents the random and repetitive vertical deviations of a real surface from its ideal or nominal form.

1.5.1 SURFACE TEXTURE

Surface texture consists of the repetitive and random deviations from the nominal surface of an object; it is defined by four features: roughness, waviness, lay, and flaws, shown in Figure 1.5.

Roughness refers to finely spaced micro-irregularities on the waves or the nominal surface.

Waviness is defined as the more frequently and uniformly spaced deviations of much larger spacing; they occur because of work deflection, vibration, heat treatment, and similar factors. Roughness is superimposed on waviness.

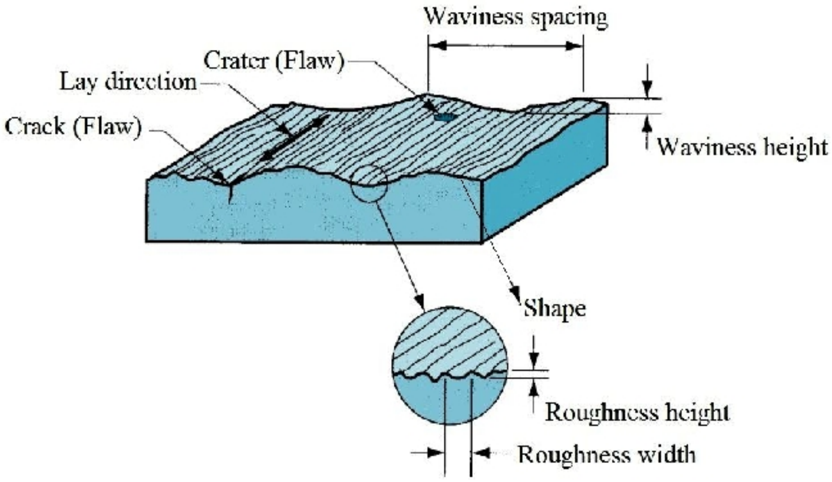


Figure 1.5 General machined surface texture

Shape is the widely spaced macroscopic deviation from the nominal contour surface.

Lay is the predominant direction or pattern of the surface texture. It is determined by the manufacturing method used to create the surface, usually from the action of a cutting tool.

Figure 1.6 presents most of the possible lays a surface can take, together with the symbol used by a designer to specify them.

Flaws are irregularities that occur occasionally on the surface; these include cracks, scratches, inclusions, and similar defects in the surface.

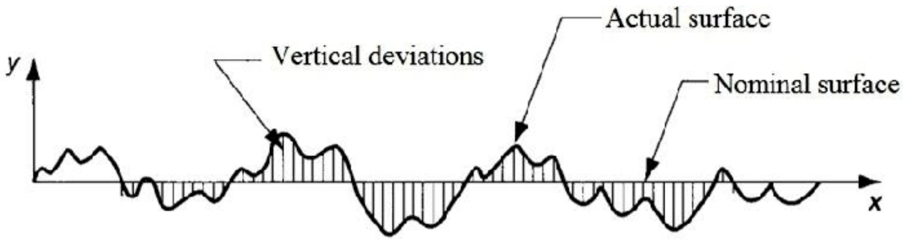


Figure 1.6 Deviations from nominal surface used in the two definitions of surface roughness.

1.5.2 SURFACE ROUGHNESS IN MACHINING

The overall roughness in a machining process is the combination of ideal roughness and natural roughness.

Ideal roughness: Ideal surface roughness is due to the feed and geometry of the tool. It represents the best possible finish which can be obtained for a given tool shape and feed. It can be achieved only if the built-up-edge, chatter and inaccuracies in the machine tool movements are eliminated completely.

Natural Roughness: One of the main factors contributing to natural roughness is the occurrence of a built-up edge. Thus, larger the built up edge, the rougher would be the surface produced, and factors tending to reduce chip-tool friction and to eliminate or reduce the built-up edge would give improved surface finish.

As the higher the feed and the smaller the tool nose radius the more prominent these marks will be. The feed marks are always important to control in finish machining, however, they are not important in rough turning.

1.5.3 FACTORS AFFECTING THE SURFACE FINISH

Whenever two machined surfaces come in contact with one another the quality of the mating parts plays an important role in the performance and wear of the mating parts. The height, shape, arrangement and direction of these surface irregularities on the work piece depend on many factors that can be grouped as follows: geometric factors, workmaterial factors and vibration and machine tool factors[6].

A) The machining variables which include

a) Cutting speed

b) Feed, and

c) Depth of cut.

B) The tool geometry

Some geometric factors which affect achieved surface finish include:

a) Nose radius

b) Rake angle

c) Side cutting edge angle

d) Cutting edge.

Tool geometry and feed combine to form the surface geometry. With the same feed, a larger nose radius causes the feed marks to be less pronounced, thus leading to a better finish. If two feeds are compared with the same nose radius, the larger feed increases the separation between feed marks, leading to an increase in the value of ideal surface roughness. If feed rate is large enough and the nose radius is small enough so that the end cutting edge participates in creating the new surface, then the end cutting-edge angle will affect surface geometry. In this case, a higher ECEA will result in a higher surface roughness value. In theory, a zero ECEA would yield a perfectly smooth surface; however, imperfections in the tool, work material, and machining process preclude achieving such an ideal finish.

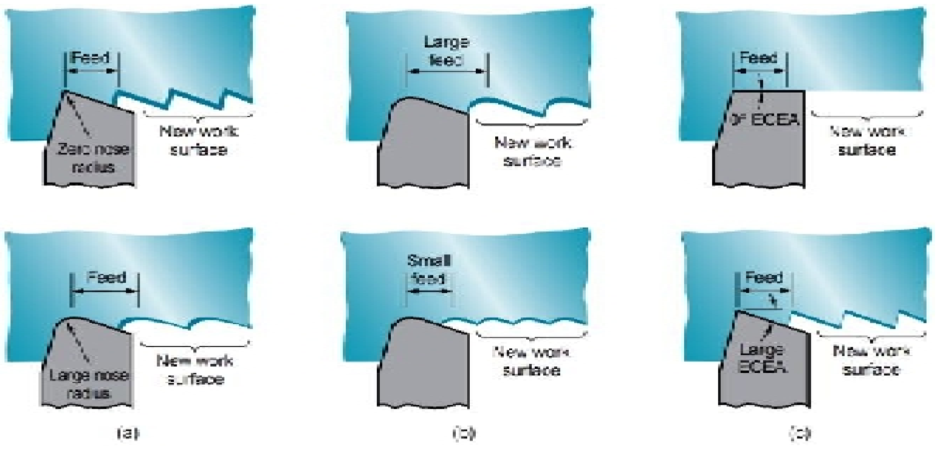


Figure 1.7 Effect of geometric factors in determining the theoretical finish on a work surface for single-point tools: (a) effect of nose radius, (b) effect of feed, and (c) effect of end cutting-edge angle.

For a sharp tool without nose radius, the maximum height of unevenness is given by:

$$R_{max} = \frac{f}{\cot\phi + \cot\beta}$$

Here f is feed rate, ϕ is major cutting edge angle and β is the minor cutting edge angle.

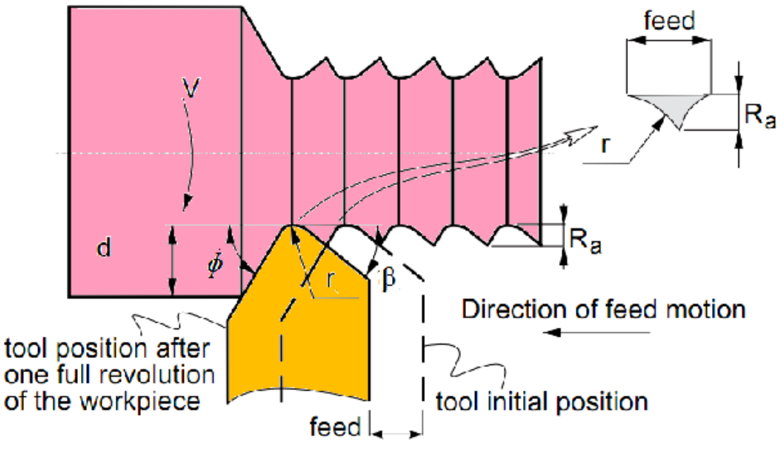


Figure 1.8 Surface roughness produced by single point tools

The effects of nose radius and feed can be combined in an equation to predict the ideal average roughness for a surface produced by a single-point tool. The equation applies to operations such as turning, shaping, and planning.

$$R_a = \frac{f^2}{32\,r}$$

Where R_a = arithmetic average surface roughness mm (in); f= feed, mm (in); and r nose radius on the tool point, mm (in).

The influence of the other process parameters is outlined below:

- Increasing the tool rake angle generally improves surface finish.
- Higher work material hardness results in better surface finish.
- Tool material has minor effect on surface finish.
- Cutting fluids affect the surface finish changing cutting temperature and as a result the built-up edge formation.
- Quality and type of the machine tool used.

- Vibrations between the work piece, machine tool and cutting tool.

Work material factors that affect finish include: (1) built-up edge effects—as the BUE cyclically forms and breaks away, particles are deposited on the newly created work surface, causing it to have a rough ‘‘sandpaper’’ texture; (2) damage to the surface caused by the chip curling back into the work; (3) tearing of the work surface during chip formation when machining ductile materials; (4) cracks in the surface caused by discontinuous chip formation when machining brittle materials; and (5) friction between the tool flank and the newly generated work surface. These workmaterial factors are influenced by cutting speed and rake angle, such that an increase in cutting speed or rake angle generally improves surface finish.

The work material factors usually cause the actual surface finish to be worse than the ideal.

Vibration and machine tool factors include chatter or vibration in the machine tool or cutting tool; deflections in the fixturing, often resulting in vibration; and backlash in the feed mechanism, particularly on older machine tools. If these machine tool factors can be minimized or eliminated, the surface roughness in machining will be determined primarily by geometric and work material factors described in the preceding. Chatter or vibration in a machining operation can result in pronounced waviness in the work surface. When chatter occurs, a distinctive noise occurs that can be recognized by any experienced machinist. Possible steps to reduce or eliminate vibration include: (1) adding stiffness and/or damping to the setup, (2) operating at speeds that do not cause cyclical forces whose frequency approaches the natural frequency of the machine tool system, (3) reducing feeds and depths to reduce forces in cutting, and (4) changing the cutter design to reduce forces. Workpiece geometry can sometimes play a role in chatter. Thin cross sections tend to increase the likelihood of chatter, requiring additional supports to alleviate the condition.

1.5.4 ROUGNESS PARAMETER

Roughness can be expressed by a number of parameters such as arithmetic average (Ra), peak-to-valley height (R_{max} or R_t), root mean squared, ten-point height (R_z) and many more. Yet, no single parameter appears to be capable of describing the surface quality adequately. In this study, arithmetic average has been adopted to represent surface roughness, as it is the most stable, frequently used and internationally accepted parameter[7]. The arithmetic average shown in figure 1.7 represents the average of the absolute deviations from the mean surface level which can be calculated using the following formula:

$$R_a = \frac{1}{L}\int_0^L |y(x)|dx$$

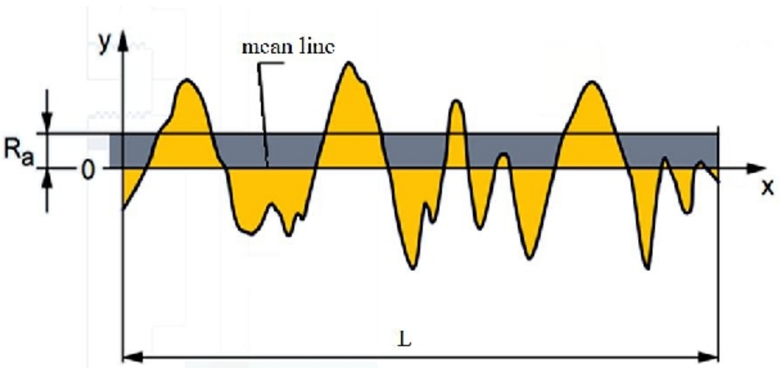


Figure 1.9 Evaluation of surface roughness Ra

Here R_a = arithmetic average roughness, y= vertical deviation from nominal surface and L= sampling length or the specified distance over which the surface deviations are measured.

Advantages of R_a

- The most commonly used parameter to monitor a production process.
- Default parameter on a drawing if not otherwise specified.
- Available even in the least sophisticated instruments.
- Statistically a very stable, repeatable parameter.

• Good for random type surfaces, such as grinding.

• A good parameter where a process is under control and where the conditions are always the same, e.g. cutting tips, speeds, feeds, cutting fluid (lubricant).

1.5.5 MEASUREMENT OF SURFACE ROUGHNESS

All the methods to assess surface roughness can be divided into three categories: (1) subjective comparison with standard test surfaces, (2) stylus electronic instruments, and (3) optical techniques.

Standard Test Surfaces: Sets of standard surface finish blocks are available, produced to specified roughness values. To estimate the roughness of a given test specimen, the surface is compared with the standard both visually and by the ‘‘fingernail test.’’ In this test, the user gently scratches the surfaces of the specimen and the standards, judging which standard is closest to the specimen. Standard test surfaces are a convenient way for a machine operator to obtain an estimate of surface roughness. They are also useful for design engineers in judging what value of surface roughness to specify on a part drawing.

Stylus Instruments: Several stylus-type instruments are commercially available to measure surface roughness directly—similar to the fingernail test, but more scientific. All profile-meters measure the physical depth of surface irregularities using some form of diamond or brush-type stylus with point radius of about 0.005mm (0.0002 in) and 90^0 tip angle is traversed across the test surface at a constant slow speed for a specified “cutoff” or sampling length, typically 0.03 inch. Most profile-meters allow for various cutoff lengths. The profile-meter transforms the vertical movement information from the stylus into an electrical signal and converts that signal into usable data that represents the topography of the surface. Profiling devices use a separate flat plane as the nominal reference against which deviations are measured. The output is a plot of the surface contour along the line traversed by the stylus. This type of system can identify both roughness and waviness in the test surface. Averaging devices reduce the roughness deviations to a single value. They use skids riding on the actual surface to establish the nominal reference plane.

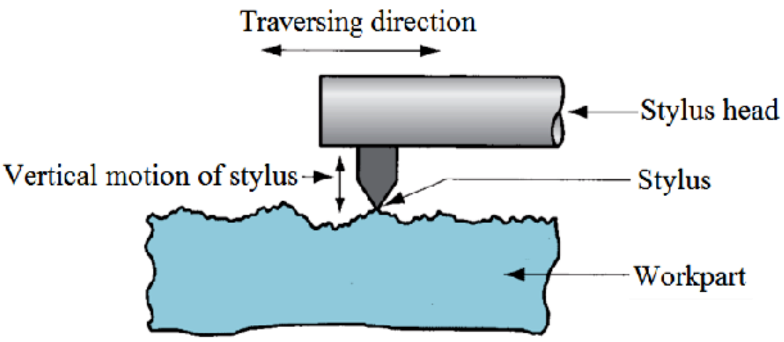


Figure 1.10 Operation of stylus-type instrument

Optical Techniques Most other surface-measuring instruments employ optical techniques to assess roughness. These techniques are based on light reflectance from the surface, light scatter or diffusion, and laser technology. They are useful in applications where stylus contact with the surface is undesirable. Some of the techniques permit very-high-speed operation, thus making 100% inspection feasible. However, the optical techniques yield values that do not always correlate well with roughness measurements made by stylus-type instruments.

1.5.6 FACTORS INFLUENCING SURFACE ROUGHNESS IN TURNING

Depth of cut:

Increasing the depth of cut increases the cutting resistance and the amplitude of vibrations. As a result, cutting temperature also rises. Therefore, it is expected that surface quality will become worse.

Feed:

As feed rate increases surface roughness also increases due to the increase in cutting force and vibration.

Cutting speed:

An increase of cutting speed generally improves surface finish.

Cutting tool wears:

The irregularities of the cutting edge due to wear are reproduced on the machined surface. Apart from that, as tool wear increases, other dynamic phenomena such as excessive vibrations will occur, thus further deteriorating surface quality.

Use of cutting fluid:

The cutting fluid is generally advantageous in regard to surface roughness as it absorbs the heat that is generated during cutting by cooling mainly the tool point and the work surface, reduces the friction between the rake face and the chip as well as between the flank and the machined surface and removes chip fragments and wear particles. Therefore, the quality of a surface machined with the presence of cutting fluid is expected to be better than that obtained from dry cutting.

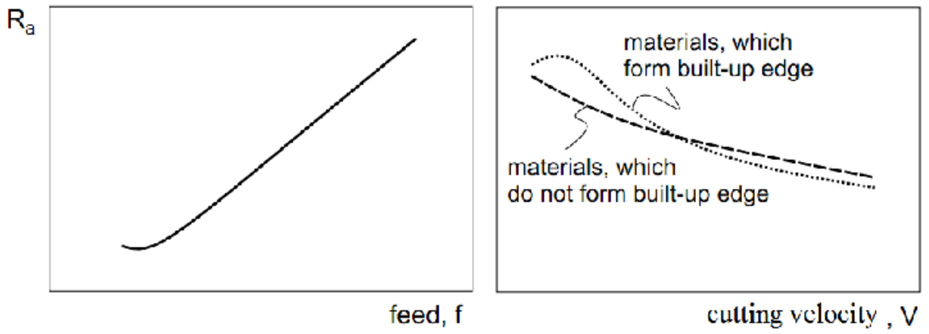


Figure 1.11 Surface roughness versus cutting speed and feed

1.6 CUTTING FORCES IN TURNING

The cutting force in turning can be resolved into three components, namely [8]

Cutting force F_Z : The main or major or Tangential component as it is the largest in magnitude. This force is in the direction of primary motion or cutting velocity vector. The cutting force constitutes about 70~80 % of the total force (F). It is also called power component as it being acting along and being multiplied by V_C decides cutting power ($P_z.V_C$) consumption.

Radial force F_Y : May not be that large in magnitude but is responsible for causing dimensional inaccuracy and vibration. It acts in the direction of radius of w/p.

Feed force F_X : It, even if larger than P_Z, is least harmful and hence least significant and acts in the direction of feed.

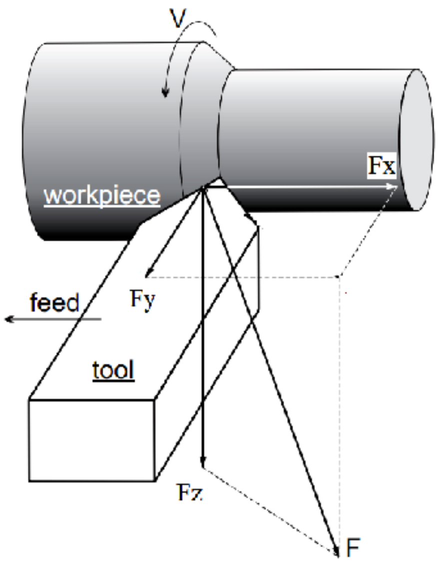


Figure 1.12 Turning force components

1.6.1 CUTTING FORCE CONTROL

The cutting force value is primarily affected by:

- Cutting conditions (cutting speed V, feed f, depth of cut d)
- Cutting tool geometry (tool orthogonal rake angle)

• Properties of work material

The simplest way to control cutting forces is to change the cutting conditions. The next diagrams show the dependencies between F_z and cutting conditions.

Cutting speed does not change significantly the cutting force F_Z. Increasing the cutting speed slightly reduces the cutting force. The dependence is more complex in the low speed range for materials, which tend to form a built-up edge. When the built-up edge disappears at high cutting speeds, the dependence is essentially the same as this for materials, which do not form a built-up edge at all.

Feed changes significantly the cutting force. The dependence is non-linear because of the so-called size effect at low feeds.

Depth of cut also changes significantly the cutting force but the dependence now is linear.

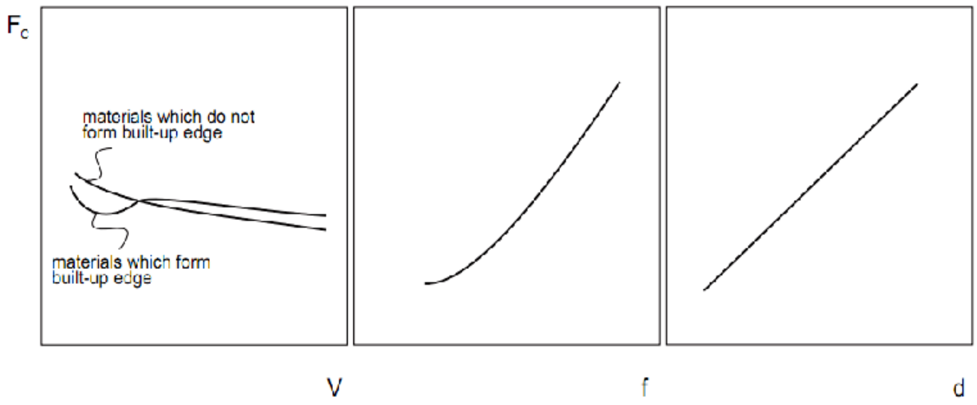


Figure 1.13 Cutting force as a function of cutting conditions

From the above it can be concluded that the most effective method of force control is to change the depth of cut and feed. If for some reasons change of the cutting conditions is not justified, machining with positive tool orthogonal rake angles will decrease significantly the cutting force but at the same time will increase the possibility of tool breakage.

1.7 TOOL WEAR

Tool wear is the rate at which the cutting edge of a tool wears away during machining due to the interactions between the tool and work piece.

There are three possible modes by which a cutting tool can fail in machining:

Fracture failure: This mode of failure occurs when the cutting force at the tool point becomes excessive, causing it to fail suddenly by brittle fracture.

Temperature failure: This failure occurs when the cutting temperature is too high for the tool material, causing the material at the tool point to soften, which leads to plastic deformation and loss of the sharp edge.

Gradual wear: Gradual wearing of the cutting edge causes loss of tool shape, reduction in cutting efficiency, an acceleration of wearing as the tool becomes heavily worn, and finally tool failure in a manner similar to a temperature failure.

1.7.1 WEAR ZONES

Gradual wear occurs at three principal location on a cutting tool. Accordingly, three main types of tool wear can be distinguished,

Crater wear: It consists of a cavity in the rake face of the tool that forms and grows from the action of the chip sliding against the surface. High stresses and temperatures characterize the tool–chip contact interface, contributing to the wearing action. The crater can be measured either by its depth or its area. Crater wear affects the mechanics of the process increasing the actual rake angle of the cutting tool and consequently, making cutting easier. At the same time, the crater wear weakens the tool wedge and increases the possibility for tool breakage. In general, crater wear is of a relatively small concern and not easily quantitative.

Flank wear appears, occurs on the flank, or relief face, of the tool. It results from rubbing between the newly generated work surface and the flank face adjacent to the cutting edge. Flank wear is measured by the width of the wear band, VB. This wear band is sometimes called the flank wear land. in the form of so-called wear land and is measured by the width of this wear land, VB, Flank wear affects to the great extend the mechanics of cutting. Cutting forces increase significantly with flank wear. If the amount of flank wear exceeds some critical value (VB > 0.5~0.6 mm), the excessive cutting force may cause tool failure.

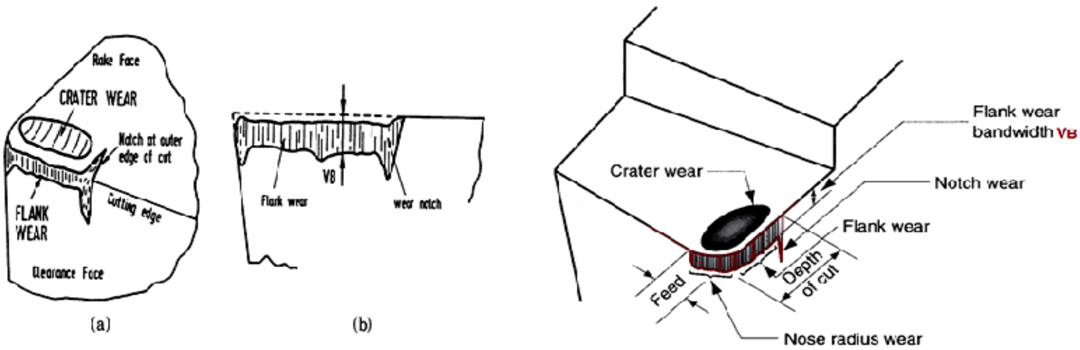


Figure 1.14 Flank wear region and measurement

TABLE 1.5 Recommended wear land size for different tool materials		
Wear (mm)	**Tool material**	**Remarks**
0.76	Carbide	Roughing passes
0.25-0.38	Carbide	Finish passes
1.25	HSS	Roughing passes
0.25-0.38	HSS	Finish passes
0.25-0.38	Cemented oxides	Roughing passes & Finish passes

Notch wear: The extreme condition of flank wear often appears on the cutting edge at the location corresponding to the original surface of the workpart. It occurs because the original work surface is harder and/or more abrasive than the internal material, which could be caused by work hardening from cold drawing or previous machining, sand particles in the surface from casting, or other reasons. As a consequence of the harder surface, wear is accelerated at this location.

Nose radius wear: A second region of flank wear that can be identified is nose radius wear; this occurs on the nose radius leading into the end cutting edge.

1.7.2 CAUSES OF TOOL WEAR

Abrasion: This is a mechanical wearing action caused by hard particles in the work material gouging and removing small portions of the tool. This abrasive action occurs in both flank wear and crater wear; it is a significant cause of flank wear.

Adhesion: When two metals are forced into contact under high pressure and temperature, adhesion or welding occur between them. These conditions are present between the chip and the rake face of the tool. As the chip flows across the tool, small particles of the tool are broken away from the surface, resulting in attrition of the surface.

Diffusion: This is a process in which an exchange of atoms takes place across a close contact boundary between two materials. In the case of tool wear, diffusion occurs at the tool–chip boundary, causing the tool surface to become depleted of the atoms responsible for its hardness. As this process continues, the tool surface becomes more susceptible to abrasion and adhesion. Diffusion is believed to be a principal mechanism of crater wear.

Chemical reaction: The high temperatures and clean surfaces at the tool–chip interface in machining at high speeds can result in chemical reactions, in particular, oxidation, on the rake face of the tool. The oxidized layer, being softer than the parent tool material, is sheared away, exposing new material to sustain the reaction process.

Plastic deformation: Another mechanism that contributes to tool wear is plastic deformation of the cutting edge. The cutting forces acting on the cutting edge at high temperature cause the edge to deform plastically, making it more vulnerable to abrasion of the tool surface. Plastic deformation contributes mainly to flank wear.

Most of these tool-wear mechanisms are accelerated at higher cutting speeds and temperatures. Diffusion and chemical reaction are especially sensitive to elevated temperature.

1.8 DRY MACHINING

Over the years, cutting fluids have been applied broadly in machining to reduce friction and wear for improving tool life and surface finish; to reduce force and energy consumption; and to cool the cutting zone, for reducing thermal distortion of the workpiece and improving tool life, and facilitating chip disposal. However, the application of cutting fluid creates serious health to the operators and environmental hazards if not disposed of properly. Dry turning is characterized by the absence of any cutting fluid. Hence, from the environmental point of view, dry turning is ecologically desirable; and from an economic view, it decreases manufacturing costs by 10 to 20%.

CHAPTER 2

LITERATURE REVIEW

OBJECTIVE AND SCOPE OF THE PRESENT WORK

2.1 LITERATURE REVIEW

Grzesik [9] has studied the effect of tribological interactions at the interface between the chipand tool on surface roughness in finish turning of C45 carbon steel.

Yang and Tarng [10] have showed that feed rate is the most significant factor affecting surface roughness in S45C steel turning. Also, with increasing feed rate, surface roughness decreases.

Aggarwal et al. [11] optimized the machining parameters of CNC turned parts combining principal component analysis with Taguchi method. In most of the approaches, the responses are considered to be uncorrelated. In practice, the responses are not independent rather they are correlated and conflicting in nature. Therefore, it is vital to study the correlation of responses before applying any method for converting multiple responses into an equivalent single response. In this study, principal component analysis (PCA) is applied on responses to obtain uncorrelated principal components (PCs).

Abouelatta and Madl [12] have found a correlation between surface roughness and cutting parameters and tool vibrations in turning considering three conventional roughness parameters viz. center line average roughness value, maximum height of the profile and skewness.

Davim [13] has presented a study of the influence of cutting parameters on the surface roughnes obtained in turning of free machining steel using Taguchi design and shown that the cutting velocity has a greater influence on the roughness followed by the feed rate.

Lin et al. [14] adopted an abdicative network to construct a prediction model for surface roughness and cutting force. Once the process parameters: cutting speed, feed rate and depth of cut were given; the surface roughness and cutting force could be predicted by this network. Regression analysis was also adopted as second prediction model for surface roughness and cutting force. Comparison was made on the results of both models indicating that adductive network was found more accurate than that by regression analysis.

Feng and Wang [15] investigated for the prediction of surface roughness in finish turning operation by developing an empirical model through considering working parameters: work piece hardness (material), feed, cutting tool point angle, depth of cut, spindle speed, and cutting time. Data mining techniques, nonlinear regression analysis with logarithmic data transformation were employed for developing the empirical model to predict the surface roughness.

Suresh et al. [16] focused on machining mild steel by TiN-coated tungsten carbide (CNMG) cutting tools for developing a surface roughness prediction model by using Response Surface Methodology (RSM). Genetic Algorithms (GA) used to optimize the objective function and compared with RSM results. It was observed that GA program provided minimum and maximum values of surface roughness and their respective optimal machining conditions.

Lee and Chen [17] highlighted on artificial neural networks (OSRR-ANN) using a sensing technique to monitor the effect of vibration produced by the motions of the cutting tool and work piece during the cutting process developed an on-line surface recognition system. The authors employed tri-axial accelerometer for determining the direction of vibration that significantly affected surface roughness then analyzed by using a statistical method and compared prediction accuracy of both the ANN and SMR.

Choudhury and Bartarya [18] focused on design of experiments and the neural network for prediction of tool wear. The input parameters were cutting speed, feed and depth of cut; flank wear, surface finish and cutting zone temperature were selected as outputs. Empirical relation between different responses and input variables and also through neural network (NN) program helped in predictions for all the three response variables and compared which method was best for the prediction.

Chien and Tsai [19] developed a model for the prediction of tool flank wear followed by an optimization model for the determination of optimal cutting conditions in machining 17-4PH stainless steel. The back-propagation neural network (BPN) was used to construct the predictive model. The genetic algorithm (GA) was used for model optimization.

Kirby et al. [20] developed the prediction model for surface roughness in turning operation. The regression model was developed by a single cutting parameter and vibrations along three axes were chosen for in-process surface roughness prediction system. By using multiple regression and Analysis of Variance (ANOVA) a strong linear relationship among the parameters (feed rate and vibration measured in three axes) and the response (surface roughness) was found. The authors demonstrated that spindle speed and depth of cut might not necessarily have to be fixed for an effective surface roughness prediction model.

Őzel and Karpat [21] studied for prediction of surface roughness and tool flank wear by utilizing the neural network model in comparison with regression model. The data set from measured surface roughness and tool flank wear were employed to train the neural network models. Predictive neural network models were found to be capable of better predictions for surface roughness and tool flank wear within the range in between they were trained.

Liao et al. [22] carried out theoretical and experimental studies to investigate the intrinsic relationship between tool flank wear and operational conditions in metal cutting processes using carbide cutting inserts. The authors developed the model to predict tool flank wear land width which combined cutting mechanics simulation and an empirical model. The study revealed that cutting speed had more dramatic effect on tool life than feed rate.

Kohli and Dixit [23] proposed a neural-network-based methodology with the acceleration of the radial vibration of the tool holder as feedback. For the surface roughness prediction in turning process the back-propagation algorithm was used for training the network model. The methodology was validated for dry and wet turning of steel using high speed steel and carbide tool and observed that the proposed methodology was able to make accurate prediction of surface roughness by utilizing small sized training and testing datasets.

Pal and Chakraborty [24] studied on development of a back propagation neural network model for prediction of surface roughness in turning operation and used mild steel work-pieces with high speed steel as the cutting tool for performing a large number of experiments. The authors used speed, feed, depth of cut and the cutting forces as inputs to the neural network model for prediction of the surface roughness. The work resulted that predicted surface roughness was very close to the experimental value.

Őzel and Karpat [25] developed models based on feed forward neural networks in predicting accurately both surface roughness and tool flank wear in finish dry hard turning.

Sing and Kumar [26] studied on optimization of feed force through setting of optimal value of process parameters namely speed, feed and depth of cut in turning of EN24 steel with TiC coated tungsten carbide inserts. The authors used Taguchi’s parameter design approach and concluded that the effect of depth of cut and feed in variation of feed force were affected more as compare to speed.

Ahmed [27] developed the methodology required for obtaining optimal process parameters for prediction of surface roughness in Al turning. For development of empirical model nonlinear regression analysis with logarithmic data transformation was applied. The developed model showed small errors and satisfactory results. The study concluded that low feed rate was good to produce reduced surface roughness and also the high speed could produce high surface quality within the experimental domain.

Abburi and Dixit [28] developed a knowledge-based system for the prediction of surface roughness in turning process. Fuzzy set theory and neural networks were utilized for this purpose. The authors developed rule for predicting the surface roughness for given process variables as well as for the prediction of process variables for a given surface roughness.

Zhong et al. [29] predicted the surface roughness of turned surfaces using networks with seven inputs namely tool insert grade, work piece material, tool nose radius, rake angle, depth of cut, spindle rate, and feed rate.

Kumanan et al. [30] proposed the methodology for prediction of machining forces using multi-layered perceptron trained by genetic algorithm (GA). The data obtained from experimental results of a turning process were explored to train the proposed artificial neural networks (ANNs) with three inputs to get machining forces as output. The optimal ANN weights were obtained using GA search. This function-replacing hybrid made of GA and ANN was found computationally efficient as well as accurate to predict the machining forces for the input machining conditions.

Mahmoud and Abdelkarim [31] studied on turning operation using High-Speed Steel (HSS) cutting tool with 450approach angle. This tool showed that it could perform cutting operation at higher speed and longer tool life than traditional tool with 900 approach angle. The study finally determined optimal cutting speed for high production rate and minimum cost, tool like, production time and operation costs.

Doniavi et al. [32] used response surface methodology (RSM) in order to develop empirical model for the prediction of surface roughness by deciding the optimum cutting condition in turning. The authors showed that the feed rate influenced surface roughness remarkably. With increase in feed rate surface roughness was found to be increased. With increase in cutting speed the surface roughness decreased. The analysis of variance was applied which showed that the influence of feed and speed were more in surface roughness than depth of cut.

Paiva et al. [33] presented a hybrid approach, combining RSM and principal component analysis (PCA) to optimize multiple correlated responses in a turning process of the AISI 1020 steel considering three input factors: cutting speed, feed rate, and depth of cut.

Kassab and Khoshnaw [34] examined the correlation between surface roughness and cutting tool vibration for turning operation. The process parameters were cutting speed, depth of cut, feed rate and tool overhanging. The experiments were carried out on lathe using dry turning (no cutting fluid) operation of medium carbon steel with different level of aforesaid process parameters. Dry turning was helpful for good correlation between surface roughness and cutting tool vibration because of clean environment. The authors developed good correlation between the cutting tool vibration and surface roughness for controlling the surface finish of the work pieces during mass production. The study concluded that the surface roughness of work piece was observed to be affected more by cutting tool acceleration; acceleration increased with overhang of cutting tool. Surface roughness was found to be increased with increase in feed rate.

Al-Ahmari [35] developed empirical models for tool life, surface roughness and cutting force for turning operation. The process parameters used in the study were speed, feed, depth of cut and nose radius to develop the machinability model. The methods used for developing aforesaid models were Response Surface Methodology (RSM) and neural networks (NN).

Thamizhmanii et al. [36] applied Taguchi method for finding out the optimal value of surface roughness under optimum cutting condition in turning SCM 440 alloy steel. The experiment was designed by using Taguchi method and experiments were conducted and results thereof were analyzed with the help of ANOVA (Analysis of Variance) method. The causes of poor surface finish as detected were machine tool vibrations, tool chattering whose effects were ignored for analyses. The authors concluded that the results obtained by this method would be useful to other researches for similar type of study on tool vibrations, cutting forces etc. The work concluded that depth of cut was the only significant factor which contributed to the surface roughness.

Natarajan et al. [37] presented the on-line tool wear monitoring technique in turning operation. Spindle speed, feed, depth of cut, cutting force, spindle-motor power and temperature were selected as the input parameters for the monitoring technique. For finding out the extent of tool wear; two methods of Hidden Markov Model (HMM) such as the Bar-graph Method and the Multiple Modeling Methods were used. A decision fusion centre algorithm (DFCA) was used for increasing the reliability of this output which combined the outputs of the individual methods to make a global decision about the wear status of the tool. Finally, all the proposed methods were combined in a DFCA to determine the wear status of the tool during the turning operations.

Ozel et al. [38] carried out finish turning of AISI D2 steels (60 HRC) using ceramic wiper (multi-radii) design inserts for surface finish and tool flank wear investigation. For prediction of surface roughness and tool flank wear multiple linear regression models and neural network models were developed. Neural network based predictions of surface roughness and tool flank wear were carried out, compared with a non-training experimental data and the results thereof showed that the proposed neural network models were efficient to predict tool wear and surface roughness patterns for a range of cutting conditions. The study concluded that best tool life was obtained in lowest feed rate and lowest cutting speed combination.

Wang and Lan [39] used Orthogonal Array of Taguchi method coupled with grey relational analysis considering four parameters viz. speed, cutting depth, feed rate, tool nose run off etc. for optimizing three responses: surface roughness, tool wear and material removal rate in precision turning on an ECOCA-3807 CNC Lathe. The MINITAB software was explored to analyze the mean effect of Signal-to-Noise (S/N) ratio to achieve the multi objective features. This study not only proposed an optimization approaches using

Orthogonal Array and grey relational analysis but also contributed a satisfactory technique for improving the multiple machining performances in precision CNC turning with profound insight.

Srikanth and Kamala [40] evaluated optimal values of cutting parameters by using a Real Coded Genetic Algorithm (RCGA) and explained various issues of RCGA and its advantages over the existing approach of Binary Coded Genetic Algorithm (BCGA). They concluded that RCGA was reliable and accurate for solving the cutting parameter optimization and construct optimization problem with multiple decision variables. These decision variables were cutting speed, feed, depth of cut and nose radius. The authors highlighted that the faster solution can be obtain with RCGA with relatively high rate of success, with selected machining conditions thereby providing overall improvement of the product quality by reduction in production cost, reduction in production time, flexibility in machining parameter selection.

Sahoo et al. [41] studied for optimization of machining parameters combinations emphasizing on fractal characteristics of surface profile generated in CNC turning operation. The authors used L27 Taguchi Orthogonal Array design with machining parameters: speed, feed and depth of cut on three different work piece materials viz. aluminum, mild steel and brass. It was concluded that feed rate was more significant influencing surface finish in all three materials. It was observed that in case of mild steel and aluminum feed showed some influences while in case of brass depth of cut was noticed to impose some influences on surface finish. The factorial interaction was responsible for controlling the fractal dimensions of surface profile produced in CNC turning.

Reddy et al. [42] adopted multiple regression model and artificial neural network to deal with surface roughness prediction model for machining of aluminium alloys by CNC turning. For judging the efficiency and ability of the model in surface roughness prediction the authors used the percentage deviation and average percentage deviation.

Wang et al. [43] studied on Hybrid Neural Network-based modeling approach integrated with an analytical tool wear model and an artificial neural network that was used to predict CBN tool flank wear in turning of hardened 52100 bearing steel. Experimental results showed that the proposed Hybrid Neural Network excelled the analytical tool wear model approach and the general neural network-based modeling approach.

Shetty et al. [44] discussed the use of Taguchi and response surface methodologies for minimizing the surface roughness in turning of discontinuously reinforced aluminum composites (DRACs) having aluminum alloy 6061 as the matrix and containing 15 vol. % of silicon carbide particles of mean diameter 25μm under pressured steam jet approach. The measured results were then collected and analyzed with the help of the commercial software package MINITAB15. The experiments were conducted using Taguchi's experimental design technique. The matrix of test conditions included cutting speeds of 45, 73 and 101 m/min, feed rates of 0.11, 0.18 and 0.25 mm/rev and steam pressure 4, 7, 10 bar while the depth of cut was kept constant at 0.5 mm. The effect of cutting parameters on surface roughness was evaluated and the optimum cutting condition for minimizing the surface roughness was also determined finally. A second order model was established between the cutting parameters and surface roughness using response surface methodology. The experimental results revealed that the most significant machining parameter for surface roughness was steam pressure followed by feed. The predicted values and measured values were fairly close, which indicated that the developed model could be effectively used to predict the surface roughness in the machining of DRACs.

2.2 OBJECTIVE AND SCOPE OF THE PRESENT WORK

Several factors directly or indirectly influence output responses in turning. The objective of this research was to investigate the effects of major input parameters on the output in dry turning and to optimize the input parameters. Again from the literature review it is evident that though some research wok was under taken into study the influence of machining input parameters on various output responses in machining of mild steel, still there exits some disparities which need to be studied with more detail. In multi-response optimization, it is very difficult to select the optimal setting which can achieve all quality requirements simultaneously. Otherwise optimizing one quality feature may lead severe quality loss to other quality characteristics which may not be accepted by the customers. In order to tackle such a multi-response optimization problem, the present study applied Taguchi method through a case study.

The objective of the present work has been formulated as follows:

i. To study the performance or effectiveness of ISO P30 grade cemented carbide insert in dry machining of AISI 1020 steel.

ii. To study the influence of cutting velocity, depth of cut, feed on flank wear, surface roughness and cutting force for a constant duration of machining for each run.

iii. Optimization approach for multiple responses (surface roughness, flank wear and cutting force) in turning using principal component analysis (PCA).

iv. Single response optimization by Taguchi method and getting the optimal cutting parameters combination.

v. ANN (artificial neural network) approach to develop a prediction model prior to the implementation of the actual machining.

vi. For better understanding we have done a comparative study to analyze the responses using coated and uncoated carbide inserts.

CHAPTER 3

EXPERIMENTATION

3.1 PLAN OF EXPERIMENT

According to the scope and objectives the present study has been done through the following plan of experiment.

a) Checking and preparing the Centre Lathe ready for performing the machining operation.
b) Cutting mild steel bar to the desired size by power saw and performing initial turning operation in Lathe to get desired dimension of the work pieces.
c) Performing straight turning operation on specimens in dry environment involving various combinations of input parameters like: cutting velocity, feed and depth of cut.
d) Measuring surface roughness with the help of a portable stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+, UK).
e) Measuring the cutting forces with the help of Kistler dynamometer.
f) Measuring cutting tool flank wear in zoom stereo optical makers microscope.

3.2 PROCESS PARAMETERS AND THEIR LEVELS

TABLE 3.1
Input parameters and their levels

Parameters	Levels		
Cutting Speed, V_C (m/min)	70	90	120
Feed rate, f (mm/rev)	0.08	0.12	0.14
Depth of cut, d (mm)	0.1	0.4	0.8
Machining Duration, s (sec)	120		

The working levels of the input parameters are based on literature survey. Taguchi's L_{27} Orthogonal Array (OA) has been selected. In the present experimental study, cutting velocity, feed and depth of cut have been considered as input parameters. The process variables with their units, notations and levels are listed in Table 3.1.

3.3 DESIGN OF EXPERIMENT

Experiments have been carried out using Taguchi's L_{27} Orthogonal Array (OA) experimental design which consists of 27 combinations of cutting velocity, feed and depth of cut. According to the design catalogue prepared by Taguchi, three process parameters (without interaction) to be varied in three finite levels.

TABLE 3.2
L27 orthogonal array

TEST	PARAMETER 1	PARAMETER 2	PARAMETER 3
1	1	1	1
2	1	1	2
3	1	1	3
4	1	2	1
5	1	2	2
6	1	2	3
7	1	3	1
8	1	3	2
9	1	3	3
10	2	1	1
11	2	1	2
12	2	1	3
13	2	2	1
14	2	2	2
15	2	2	3
16	2	3	1
17	2	3	2
18	2	3	3
19	3	1	1
20	3	1	2
21	3	1	3
22	3	2	1
23	3	2	2
24	3	2	3
25	3	3	1
26	3	3	2
27	3	3	3

3.4 EQUIPMENTS USED

3.4.1 CENTRE LATHE

The turning experiments were carried out using uncoated cemented carbide inserts in a HMT NH26 lathe machine. The complete experiment setup with lathe, dynamometer, amplifier, workpiece is shown in the Figure 3.1.

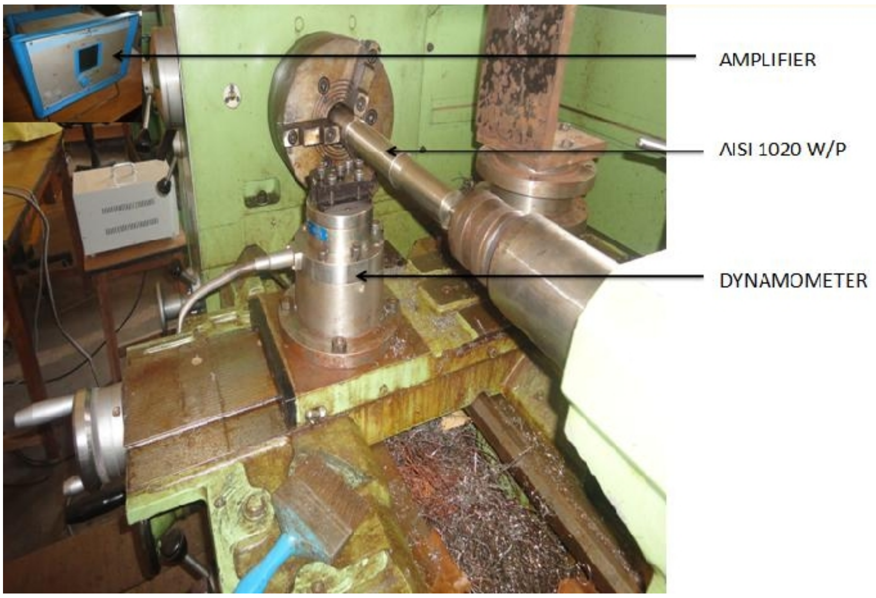


Figure 3.1 Experimental setup

TABLE 3.3 Lathe Specifications	
Machine type	Horizontal
Control	Manual
Number of axes	2
Cutting diameter	584 mm
Cutting length	3050 mm
Bar /bore	89 mm
Tool stations	04
Spindle	01
Motor power	11 kW
Spindle speed	1800 RPM

3.4.2 DYNAMOMATER

a) Four-component dynamometer for measuring a torque Mz and the three orthogonal components of a force.

b) The dynamometer has a great rigidity and consequently a high natural frequency.

c) Compact and robust multi-component force measuring instrument.

d) Suitable for cutting force measurements when drilling.

e) Universal in use.

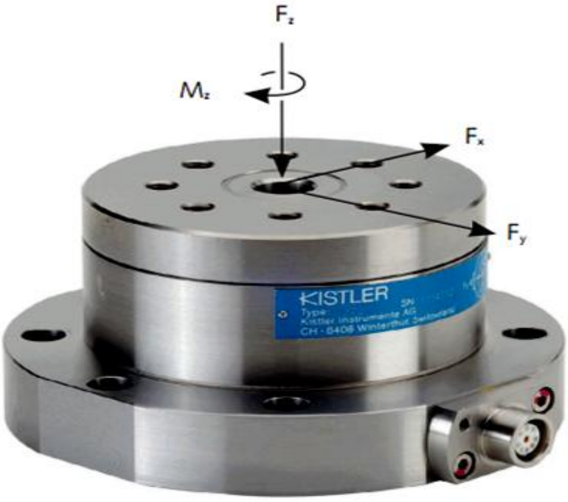


Figure 3.2 Dynamometer

Figure 3.3 Multichannel charge amplifier

3.4.3 PROFILOMETER

Roughness measurement has been done using a portable stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+, UK) shown in Figure 2.2. The Talysurf instrument (Surtronic 3+) is a portable, self-contained instrument for the measurement of surface texture. The parameter evaluations are microprocessor based. The measurement results are displayed on an LCD screen. The instrument is powered by non-rechargeable alkaline battery (9V). It is equipped with a diamond stylus having a tip radius 5 µm. The measuring stroke always starts from the extreme outward position. At the end of the measurement the pickup returns to the position ready for the next measurement. The selection of cut-off length determines the traverse length. Usually as a default, the traverse length is five times the cut-off length though the magnification factor can be changed. The profilometer has been set to a cut-off length of 0.8 mm, filter 2CR, and traverse speed 1 mm/sec and 4 mm traverse length. The measured profile has been digitized and processed through the dedicated advanced surface finish analysis software Talyprofile for evaluation of the roughness parameters. Surface roughness measurement with the help of stylus has been shown in Figure 3.4.

Figure 3.4 Talysurf profilometer

3.4.4 MEASUREMENT OF TOOL FLANK WEAR

Flank wear is quantified easily as compared to other type of tool wear. Depth of flank wear has been measured by stereo optical microscope shown in Figure 3.5.

Figure 3.5 Optical microscope

3.5 CUTTING TOOL

Description: P30 carbide inserts uncoated and coated (TiN-TiCN-Al_2O_3-ZrCN CVD) types are used for the experiment.

Tool Designation

SCMT 12 04 08

S - Insert Shape = 90^o; C – Clearance Angle = 7^o; M – Medium Tolerance = +/- 0.005"; T – Insert Features (Counter sinking hole with chip groove on top surface for easy flow of chip over rake surface); 12 – 12 means length of each cutting edge is 12 mm; 04 – 04 stands for nominal thickness of the insert is 4 mm; 08 – 08 stands for nose radius = 0.8 mm.

The composition of P30 uncoated carbide inserts WC 74.25%, TiC 8.25%, Ta +NbC 8.80%, and Co 8.70%

3.6 TOOL HOLDER

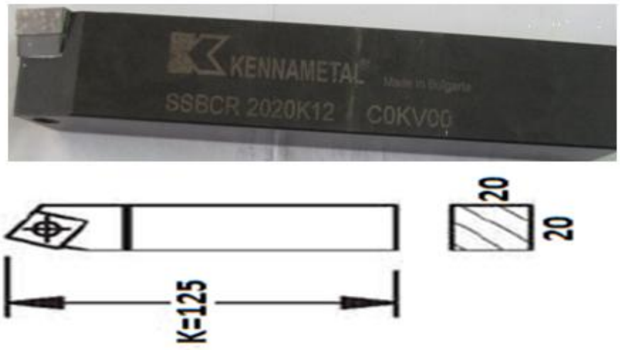


Figure 3.6 ISO SSBR 2020K12 tool holder

3.4. WORKPIECE

AISI 1020 steel bar of 50 mm diameter and 350 mm length is used. The composition of AISI 1020 is listed in weight percentage as C 0.23%, Mn 0.60%, P 0.04%, S 0.5% and Fe remaining. The properties are given in Table 3.4. It is used in bullets, automotive industries, nuts and bolts, chain, hingers, knives, amours, pipes, magnets and many other applications.

TABLE 3.4
Properties of AISI 1020 steel

Density (Kg/m^3)	7.7-8.03 x 10^3
Poisson's Ratio	0.27-0.30
Elastic Modulus (GPa)	190-210
Tensile Strength (MPa)	394.7
Yield Strength (MPa)	294.8
Elongation (%)	36.5
Reduction in Area (%)	66
Hardness (HB)	111
Impact Strength (Izod) (J)	123.4

3.5 SEM STUDY OF INSERTS

Scanning Electron Microscope (SEM): Electron Microscope to study the sample's surface topography (surface shapes and features), composition.

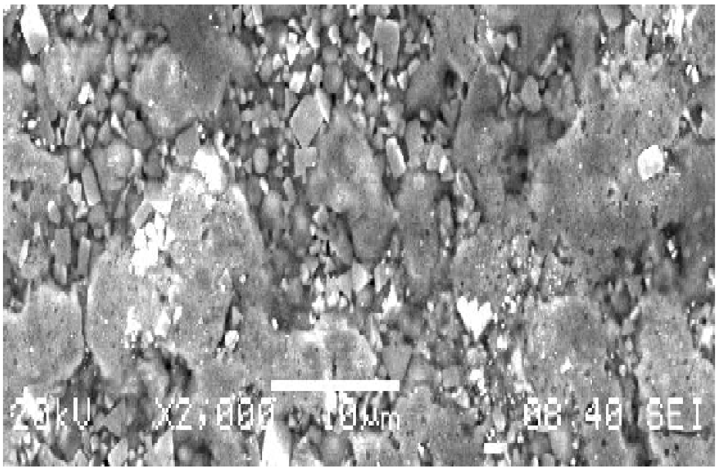


Figure 3.7 SEM image of uncoated inserts

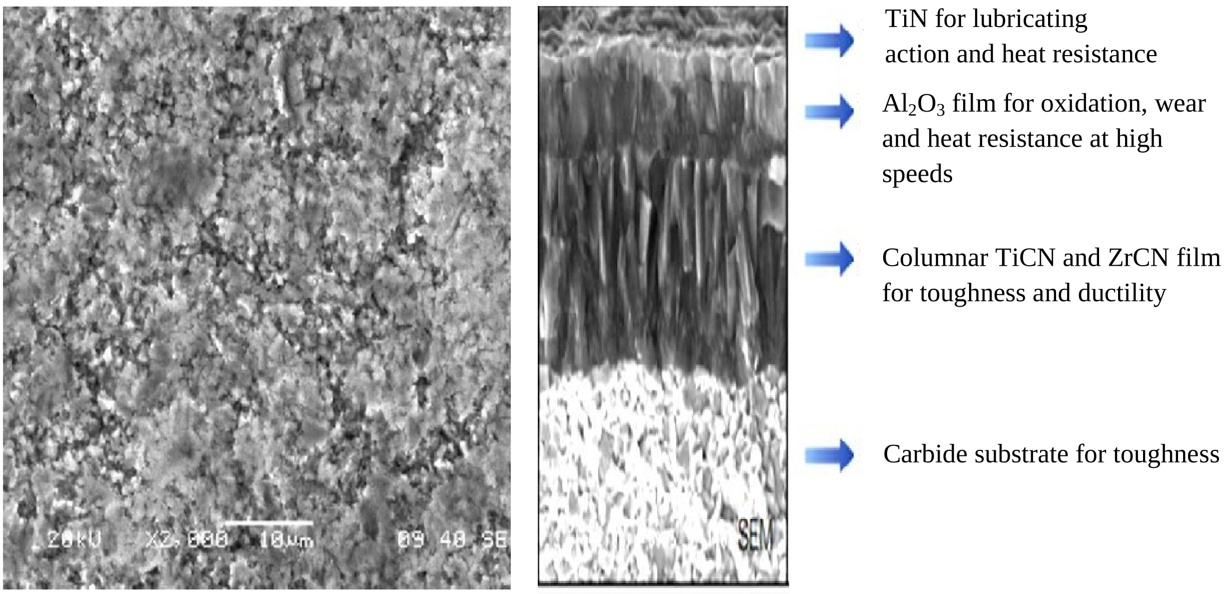
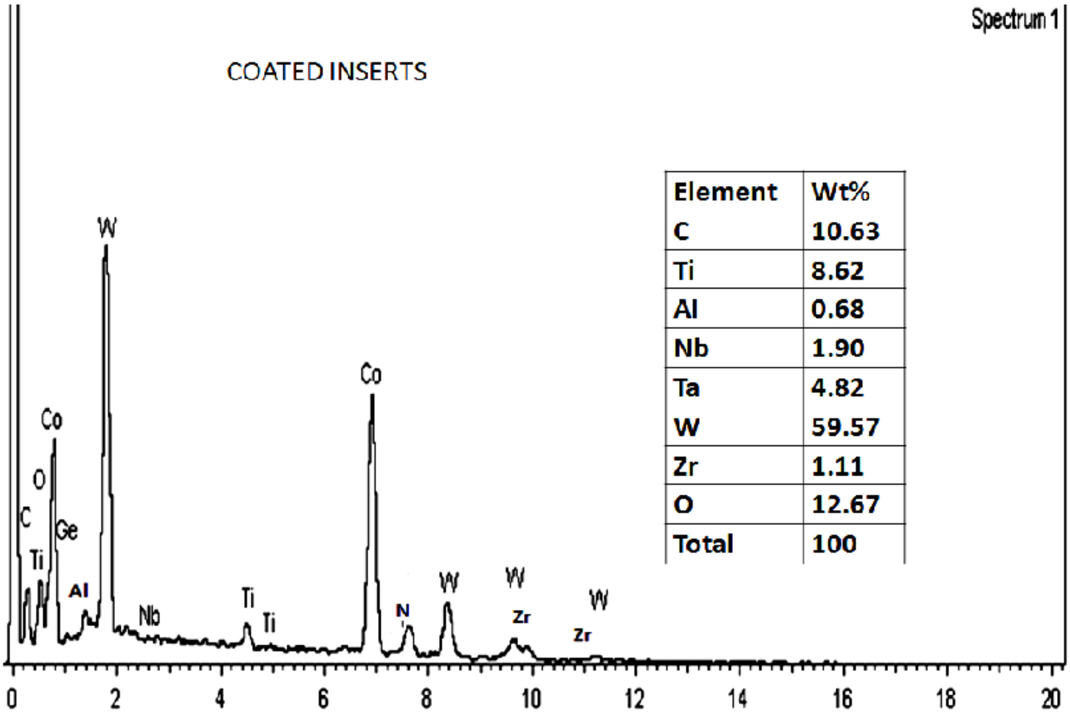


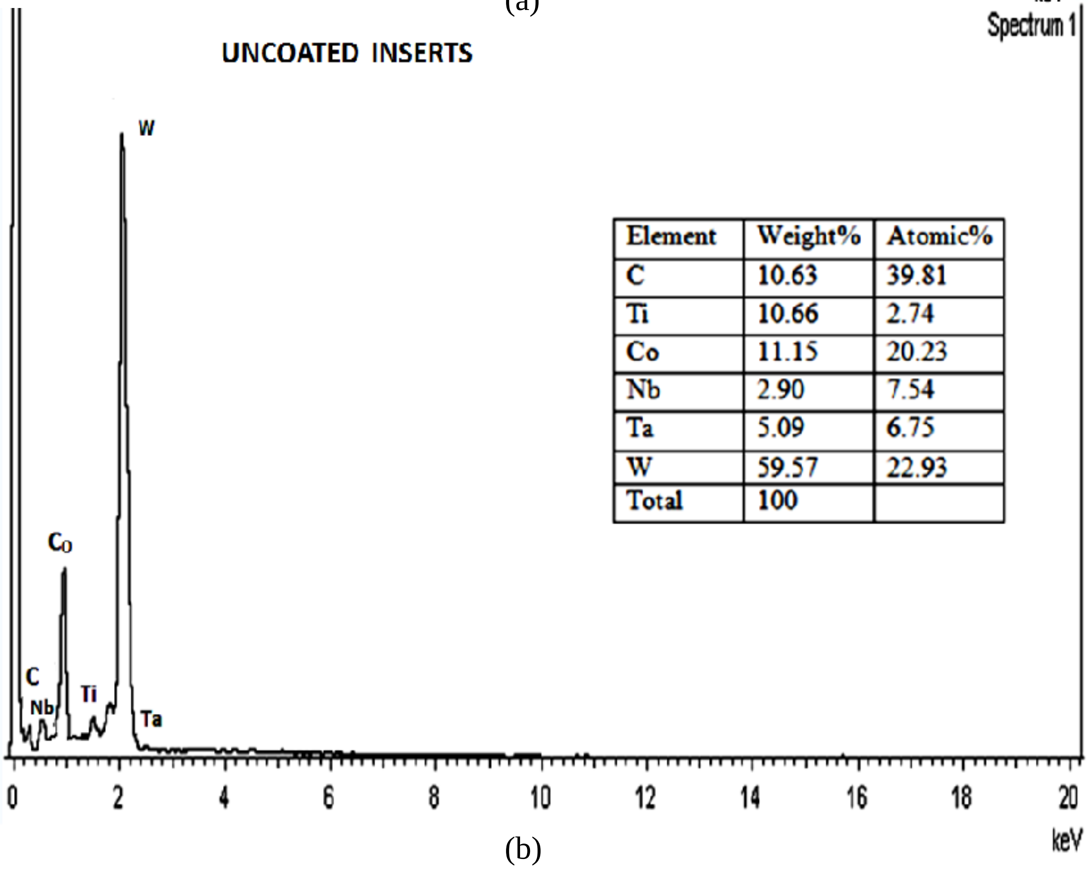
Figure 3.8 SEM image of coated inserts

These SEM images of the coated inserts are darker and denser than uncoated due to the presence of (η) phase carbides and coating materials. These phases consist of carbides of W and Co with chemical. These η phase carbides which are relatively harder provide greater wear resistance.



Element	Wt%
C	10.63
Ti	8.62
Al	0.68
Nb	1.90
Ta	4.82
W	59.57
Zr	1.11
O	12.67
Total	100

(a)



Element	Weight%	Atomic%
C	10.63	39.81
Ti	10.66	2.74
Co	11.15	20.23
Nb	2.90	7.54
Ta	5.09	6.75
W	59.57	22.93
Total	100	

(b)

Figure 3.9 Representative EDS spectra for (a) coated and (b) uncoated inserts

3.5 DATA COLLECTION

MS bar required for conducting the experiment has been prepared first. Then, using different levels of the process parameters 27 numbers of runs are done. Then surface roughness and surface profile have been measured precisely with the help of a portable stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+, UK). The results of the experiments have been shown in Table 3.5. Analysis has been made based on those experimental data in the following chapter. Optimization of surface roughness, Cutting force and flank wear of the cutting tool has been made by WPCA and Taguchi method. Confirmatory tests have also been conducted finally to validate optimal results.

TABLE 3.5
Experimental results

				Coated inserts					Uncoated inserts				
Sl. no	**Vc m/min**	**f mm/rev**	**d mm**	**Ra μm**	**VB mm**	**Fx N**	**Fy N**	**Fz N**	**Ra μm**	**VB mm**	**Fx N**	**Fy N**	**Fz N**
1	70	0.08	0.1	1.93	0.074	34.80	50.20	78.68	2.66	0.098	69.34	84.13	103.54
2	70	0.08	0.4	2.02	0.080	91.70	116.20	119.78	2.78	0.110	178.38	194.34	157.49
3	70	0.08	0.8	2.07	0.079	171.55	144.91	185.90	2.86	0.108	331.30	242.09	245.81
4	70	0.12	0.1	2.49	0.081	89.99	195.33	152.13	3.45	0.112	174.39	325.46	202.02
5	70	0.12	0.4	2.59	0.084	95.60	253.09	217.81	3.57	0.118	184.97	422.74	289.37
6	70	0.12	0.8	2.63	0.082	50.92	60.32	252.75	3.64	0.114	99.27	100.34	335.68
7	70	0.14	0.1	3.25	0.083	76.56	132.93	162.60	4.49	0.116	148.71	221.48	218.46
8	70	0.14	0.4	3.34	0.085	115.63	104.82	210.00	4.62	0.120	223.83	174.68	281.57
9	70	0.14	0.8	2.65	0.072	65.32	59.66	182.56	3.15	0.121	105.12	150.32	208.15
10	90	0.08	0.1	1.65	0.083	30.89	47.66	64.43	2.27	0.116	61.23	79.86	83.07
11	90	0.08	0.4	1.88	0.086	41.64	105.12	89.38	2.60	0.122	82.06	175.15	116.19
12	90	0.08	0.8	1.93	0.079	50.67	66.96	103.56	2.67	0.108	99.51	112.00	136.12
13	90	0.12	0.1	2.16	0.080	54.09	94.80	106.01	2.99	0.110	105.87	157.89	140.05
14	90	0.12	0.4	2.30	0.084	125.40	74.63	159.20	3.18	0.118	242.68	124.34	211.53
15	90	0.12	0.8	2.40	0.081	90.23	72.84	187.29	3.32	0.112	175.67	121.37	249.24
16	90	0.14	0.1	2.63	0.087	37.24	95.76	122.02	3.64	0.124	73.73	159.74	163.43
17	90	0.14	0.4	2.77	0.078	102.69	165.99	207.48	3.84	0.106	198.98	277.18	278.46
18	90	0.14	0.8	2.91	0.082	83.88	59.07	211.72	4.03	0.114	163.08	99.54	283.50
19	120	0.08	0.1	1.42	0.083	41.64	132.05	85.53	1.95	0.116	82.06	220.66	111.44
20	120	0.08	0.4	1.55	0.086	105.86	71.13	158.54	2.15	0.122	205.17	118.59	211.09
21	120	0.08	0.8	1.59	0.087	108.79	133.85	139.31	2.21	0.124	210.70	222.89	182.70
22	120	0.12	0.1	2.02	0.085	58.00	44.74	120.92	2.80	0.120	113.28	74.55	159.67
23	120	0.12	0.4	2.16	0.086	39.68	42.41	123.37	2.99	0.122	78.01	70.57	163.17
24	120	0.12	0.8	2.21	0.080	58.24	52.90	138.83	3.06	0.110	114.15	88.17	184.96
25	120	0.14	0.1	2.54	0.083	47.01	44.14	153.52	3.51	0.116	92.68	73.51	205.70
26	120	0.14	0.4	2.63	0.081	50.18	58.18	150.37	3.64	0.112	98.88	96.99	202.30
27	120	0.14	0.8	2.73	0.088	74.12	56.20	198.03	3.77	0.126	144.42	93.70	265.66

CHAPTER 4

RESULTS AND DISCUSSION

4.1 PRINCIPAL COMPONENT ANALYSIS (PCA)

Taguchi method cannot solve a multi-objective optimization problem. In practical case quality attributes shouldn't be uncorrelated or independent. So We applied Principal Component analysis (PCA) to eliminate response correlation that exists between the responses and to evaluate independent or uncorrelated quality indices called Principal Components [45]. Principal Component Analysis (PCA), [46] is a way of identifying correlated data patterns and expressing the data with their similarities and differences. The main advantage of PCA is that once the patterns in data have been identified, the data can be compressed, i.e. by reducing the number of dimensions, without much loss of information. The methods involved in PCA are discussed below:

1) Getting some data
2) Normalization of data
3) Determination of correlation coefficient array.
4) Determination of Eigen values and Eigen vectors
5) Evaluation of principal components

Normalization of the data provides fair information for determining the optimal levels of process parameters. The original data are converted to a range 0 to 1 with 1 counting the best performance and 0 the worst. The normalization procedure for higher-the-better characteristic is given in equation:

$$X_i^*(k) = \frac{X_i(k)}{\max X_i(k)}$$

$$\text{Here, } \begin{array}{l} i = 1, 2, \ldots\ldots\ldots, m; \\ k = 1, 2, \ldots\ldots\ldots, n \end{array}$$

Assuming, the number of experimental runs in Taguchi's OA design is m, and the number of quality characteristics is n. $X_i^*(k)$ is the normalized data of the k th element in the i th sequence.

TABLE 4.1
Normalized data

Coated inserts					Uncoated inserts				
Ra µm	**VB mm**	**Fx N**	**Fy N**	**Fz N**	**Ra µm**	**Vb mm**	**Fx N**	**Fy N**	**Fz N**
0.570	0.841	0.203	0.198	0.311	0.568	0.778	0.209	0.199	0.308
0.598	0.909	0.535	0.459	0.474	0.594	0.873	0.538	0.460	0.469
0.612	0.898	1.000	0.573	0.736	0.611	0.857	1.000	0.573	0.732
0.737	0.920	0.525	0.772	0.602	0.737	0.889	0.526	0.770	0.602
0.765	0.955	0.557	1.000	0.862	0.763	0.937	0.558	1.000	0.862
0.779	0.932	0.297	0.238	1.000	0.778	0.905	0.300	0.237	1.000
0.962	0.943	0.446	0.525	0.643	0.958	0.921	0.449	0.524	0.651
0.987	0.966	0.674	0.414	0.831	0.987	0.952	0.676	0.413	0.839
1.001	0.932	0.381	0.236	0.852	1.000	0.905	0.384	0.235	0.861
0.488	0.943	0.180	0.188	0.255	0.485	0.921	0.185	0.189	0.247
0.556	0.977	0.243	0.415	0.354	0.556	0.968	0.248	0.414	0.346
0.570	0.898	0.295	0.265	0.410	0.569	0.857	0.300	0.265	0.406
0.640	0.909	0.315	0.375	0.419	0.639	0.873	0.320	0.373	0.417
0.681	0.955	0.731	0.295	0.630	0.679	0.937	0.733	0.294	0.630
0.709	0.920	0.526	0.288	0.741	0.708	0.889	0.530	0.287	0.742
0.779	0.989	0.217	0.378	0.483	0.778	0.984	0.223	0.378	0.487
0.820	0.886	0.599	0.656	0.821	0.819	0.841	0.601	0.656	0.830
0.862	0.932	0.489	0.233	0.838	0.861	0.905	0.492	0.235	0.845
0.420	0.943	0.243	0.522	0.338	0.417	0.921	0.248	0.522	0.332
0.459	0.977	0.617	0.281	0.627	0.459	0.968	0.619	0.281	0.629
0.470	0.989	0.634	0.529	0.551	0.472	0.984	0.636	0.527	0.544
0.598	0.966	0.338	0.177	0.478	0.597	0.952	0.342	0.176	0.476
0.640	0.977	0.231	0.168	0.488	0.639	0.968	0.235	0.167	0.486
0.654	0.909	0.339	0.209	0.549	0.653	0.873	0.345	0.209	0.551
0.751	0.943	0.274	0.174	0.607	0.750	0.921	0.280	0.174	0.613
0.779	0.920	0.293	0.230	0.595	0.778	0.889	0.298	0.229	0.603
0.807	1.000	0.432	0.222	0.783	0.806	1.000	0.436	0.222	0.791

TABLE 4.2
Correlation

Coated inserts						Uncoated inserts					
Correlation coefficient	**Ra PC1**	**VB PC2**	**Fx PC3**	**Fy PC4**	**Fz PC5**	**Correlation coefficient**	**Ra PC1**	**VB PC2**	**Fx PC3**	**Fy PC4**	**Fz PC5**
C1	0.481	-0.529	-0.252	0.343	-0.554	C1	0.489	0.519	-0.247	-0.338	-0.563
C2	0.042	-0.304	0.948	0.063	-0.067	C2	0.042	0.303	0.948	-0.059	-0.065
C3	0.503	0.421	0.125	-0.622	-0.409	C3	0.498	-0.428	0.127	0.632	-0.396
C4	0.363	0.614	0.142	0.681	0.086	C4	0.357	-0.619	0.145	-0.682	0.083
C5	0.618	-0.27	-0.053	-0.165	0.717	C5	0.622	0.273	-0.055	0.156	0.718

TABLE 4.3 Eigenvalues and eigenvectors (Coated inserts)					
	ψ1	**ψ2**	**ψ3**	**ψ4**	**ψ5**
Eigenvalues	2.097	1.179	0.985	0.555	0.182
Eigenvector	0.481	-0.529	-0.252	0.343	-0.554
	0.042	-0.304	0.948	0.063	-0.067
	0.503	0.421	0.125	-0.622	-0.409
	0.363	0.614	0.142	0.681	0.086
	0.618	-0.27	-0.053	-0.165	0.717
AP	0.419	0.236	0.197	0.111	0.04
CAP	0.419	0.655	0.852	0.964	1.00

TABLE 4.4 Eigenvalues and eigenvectors (Unoated inserts)					
	ψ1	**ψ2**	**ψ3**	**ψ4**	**ψ5**
Eigenvalues	2.096	1.187	0.984	0.555	0.176
Eigenvector	0.489	0.519	-0.247	-0.338	-0.563
	0.042	0.303	0.948	-0.059	-0.065
	0.498	-0.428	0.127	0.632	-0.396
	0.357	-0.619	0.145	-0.682	0.083
	0.622	0.273	-0.055	0.156	0.718
AP	0.419	0.237	0.197	0.111	0.04
CAP	0.419	0.875	0.645	0.714	1.00

AP=Accountability proportion; CAP= Cumulative accountability proportion; ψ=principal component

TABLE 4.5
Evaluation of principal components

Coated inserts					Uncoated inserts				
pc1	**pc2**	**pc3**	**pc4**	**pc5**	**pc1**	**pc2**	**pc3**	**pc4**	**pc5**
0.676	-0.434	0.691	0.206	-0.215	0.677	0.401	0.635	-0.193	-0.114
1.054	-0.214	0.818	0.164	-0.231	1.050	0.184	0.790	-0.152	-0.116
1.497	-0.023	0.864	-0.087	-0.232	1.491	-0.008	0.831	0.098	-0.111
1.309	-0.137	0.830	0.411	-0.187	1.308	0.113	0.806	-0.400	-0.070
1.584	-0.079	0.878	0.515	-0.012	1.582	0.054	0.868	-0.507	0.112
1.267	-0.694	0.705	0.138	0.122	1.272	0.673	0.683	-0.133	0.240
1.315	-0.459	0.748	0.363	-0.272	1.321	0.436	0.733	-0.350	-0.147
1.518	-0.502	0.766	0.125	-0.256	1.527	0.482	0.759	-0.114	-0.125
1.324	-0.738	0.667	0.185	-0.142	1.336	0.716	0.646	-0.175	-0.018
0.591	-0.422	0.807	0.201	-0.208	0.589	0.401	0.790	-0.192	-0.093
0.800	-0.330	0.857	0.326	-0.184	0.798	0.313	0.853	-0.317	-0.065
0.810	-0.398	0.760	0.181	-0.180	0.810	0.372	0.726	-0.171	-0.071
0.900	-0.365	0.771	0.266	-0.211	0.900	0.341	0.742	-0.255	-0.099
1.232	-0.332	0.833	-0.064	-0.263	1.232	0.311	0.821	0.075	-0.135
1.207	-0.457	0.761	0.048	-0.114	1.211	0.433	0.736	-0.037	0.006
0.961	-0.519	0.796	0.372	-0.208	0.969	0.504	0.797	-0.362	-0.081
1.478	-0.270	0.758	0.276	-0.114	1.484	0.241	0.721	-0.265	0.006
1.302	-0.616	0.716	0.071	-0.119	1.312	0.593	0.695	-0.063	0.005
0.762	-0.178	0.875	0.352	-0.108	0.758	0.156	0.859	-0.342	0.009
1.062	-0.277	0.895	-0.077	-0.098	1.064	0.263	0.889	0.085	0.034
1.119	-0.107	0.944	0.098	-0.146	1.115	0.092	0.944	-0.091	-0.019
0.858	-0.488	0.807	0.097	-0.176	0.860	0.471	0.798	-0.088	-0.054
0.828	-0.567	0.792	0.171	-0.150	0.831	0.552	0.787	-0.162	-0.027
0.939	-0.499	0.740	0.122	-0.150	0.944	0.476	0.710	-0.111	-0.034
0.977	-0.625	0.732	0.165	-0.141	0.987	0.606	0.715	-0.154	-0.019
1.011	-0.588	0.714	0.202	-0.166	1.022	0.566	0.689	-0.189	-0.047
1.212	-0.624	0.789	0.093	-0.110	1.223	0.611	0.793	-0.084	0.025

4.2 WEIGHTED PRINCIPAL COMPONENT ANALYSIS

In order to determine the optimum factor level setting that maximizes the performance of the quality characteristics in a single setting, weighted principal component analysis is applied for combining multiple responses into a single response known as MPCI.

This WPCA method follows the same steps as like PCA to calculate the principal components/principal component scores (PCs). In addition to this, it uses the variance (proportion explained) to calculate the MPCI without following to the complex fuzzy inference system like in the hybrid approach. The analysis combines the variables that account for the largest amount of variance to form the first principal component. The second principal component accounts for the next largest amount of variance, and so on until the total sample variance is combined into component groups. In a multiple responses case, the responses need to be converted into an equivalent single response for analysis purpose.

For calculation of weighted principal components, the initial step is to calculate the principal components (PCs). The PCs are calculated as per the steps prescribed in PCA. Principal components are independent (uncorrelated) of each other. Simultaneously, the explained variance of each principal component for the total variance of the responses is also obtained. Next, in weighted principal component method, all principal components will be used; thus the explained variance can be completely explained in all responses. Since different principal components have their own variance to account for the total variance, the variance of each principal component is regarded as the individual priority weight [47]. Because these principal components are independent to each other, an additive model can be developed by simply adding all principal components to represent multi-response performance characteristic index (MPCI). Therefore, MPCI is given as:

$$MPCI = \sum_{k=1}^{n} Y_{mk} W_k$$

where Y_{mk} is the uncorrelated Principal components and W_k is the weight of *k*th principal components. The weighted principal component analysis provides weights (Variance explained by each component) for each principal component to be extracted from data rather than restoring arbitrary and ambiguous method of assigning weights for conventional multi-responses into equivalent single responses (MPCI) given in Table 4.5. The larger the MPCI is the higher the quality. The MPCI is further analyzed by Taguchi method and optimal parameter settings are obtained. Finally, with the application of ANOVA (Analysis of Variance), significant factors in this quality index and their contribution percentage for total variation in MPCI can be obtained.

TABLE 4.6
MPCI values

	Coated inserts		**Uncoated inserts**	
Sl.No	**Proportion**	**MPCI**	**Proportion**	**MPCI**
1	0.419 0.236 0.197 0.111 0.036	0.332	0.419 0.237 0.197 0.111 0.036	0.479
2		0.562		0.618
3		0.774		0.794
4		0.718		0.687
5		0.875		0.794
6		0.526		0.821
7		0.621		0.757
8		0.673		0.886
9		0.528		0.837
10		0.322		0.473
11		0.456		0.539
12		0.409		0.549
13		0.465		0.572
14		0.585		0.755
15		0.549		0.751
16		0.471		0.640
17		0.731		0.792
18		0.545		0.820
19		0.485		0.486
20		0.544		0.694
21		0.636		0.664
22		0.408		0.618
23		0.383		0.615
24		0.429		0.634
25		0.419		0.680
26		0.442		0.675
27		0.522		0.805

4.3 TAGUCHI METHOD

In determining the effectiveness of a design, we must develop a measure that can evaluate the impact of the design parameters on the output quality characteristics. This measure is introduced by Dr. Genichi Taguchi and called "*Taguchi's philosophy*". It is an efficient tool for the design of high quality manufacturing system. It is a widely accepted methodology for contemporary experiment design. The Taguchi method can optimize performance characteristics through the settings of process parameters and reduce the sensitivity of the system performance to sources of variation [48]. As a result, the Taguchi method has become a powerful tool in the design of experiment methods. In order to evaluate the optimal parameter setting, Taguchi method uses a statistical measure of performance called signal-to-noise (S/N) ratio that takes both the mean and the variability into account. Formerly, The S/N ratio was an electrical engineering concept defined as the ratio of signal power to noise power corrupting the signal. Taguchi expands this conception to the engineering system design area. The philosophy of Taguchi methods stresses that every engineering system is a man-made system, which employs energy transformation to convert input signal(s) into specific intended function. The ratio depends on the quality characteristics of the product/process to be optimized. The optimal setting is the parametric combination that results in highest S/N ratio. Usually, there are three categories of signal-to- noise ratios such as lower-the-better (LTB), the higher-the-better (HTB), and nominal-the-best (NTB) [49]. In this study, four responses such as material removal rate (MRR), tool wear rate (TWR), surface roughness (Ra) and circularity of machined component are considered. Two responses like surface roughness and tool wear rate are to be minimized whereas two responses like material removal rate and circularity are to be maximized. Therefore, HTB and LTB categories of S/N ratios are dealt here.

The higher-the-better (HTB) S/N ratio is given by

$$\text{HTB S/N Ratio} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right)$$

The lower-the-better (LTB) S/N ratio is given as

$$\text{LTB S/N Ratio} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right)$$

where denotes the value of the response for replicate i and n is the number of replicates. The S/N ratio measures the level of system performance and the higher value gives more robustness of the system.

However, Taguchi method is concerned with the optimization of a single performance characteristic. Handling the more demanding multiple performance characteristics are still an interesting research problem. Researchers have suggested different multi-response optimization techniques but some proposed methods increases uncertainties due to unknown correlations among the objectives or multi performance characteristics (MPCs). To solve the correlation problem, PCA is an advisable statistical technique to examine the correlation within the MPCs. A new set of uncorrelated data of MPC, called principal components, could be derived by PCA to explain the variance by generating principal component scores. Now it is fruitful to apply any multi-objective optimization methods to the process by converting the multi-responses into a single index i.e. multi-response performance characteristic index (MPCI). Fuzzy logic and weighted principal component analysis will be used to calculate the MPCI value in two different ways. Then, Taguchi method can be used to analyze MPCI to obtain best parameter setting which simultaneously optimizes multiple responses.

4.3.1 ANALYSIS OF VARIANCE AND MAIN EFFCET PLOT

From the ANOVA table it is found that cutting velocity is the most influencing parameter for minimizing responses followed by feed in both the tool conditions.

TABLE 4.7 Analysis of variance for coated inserts					
Source	**SS**	**MS**	**F**	**P**	**%C**
Vc	0.1122	0.0561	3.82	0.039	50.534
f	13.8758	0.2036	0.86	0.063	27.668
d	0.4071	6.9379	29.24	0.161	19.854
Residual Error	0.2931	0.0146			1.944
Total					100

TABLE 4.8 Analysis of variance for uncoated inserts					
Source	**SS**	**MS**	**F**	**P**	**%C**
Vc	0.0464	0.0232	6.63	0.044	62.792
f	0.1433	0.0716	19.52	0.065	20.623
d	0.0999	0.0499	13.65	0.119	14.983
Residual Error	0.0731				1.600
Total					100

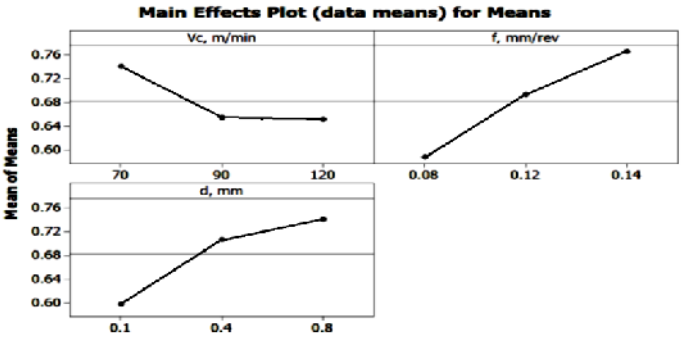


Figure 4.1 Main effect plot for coated inserts

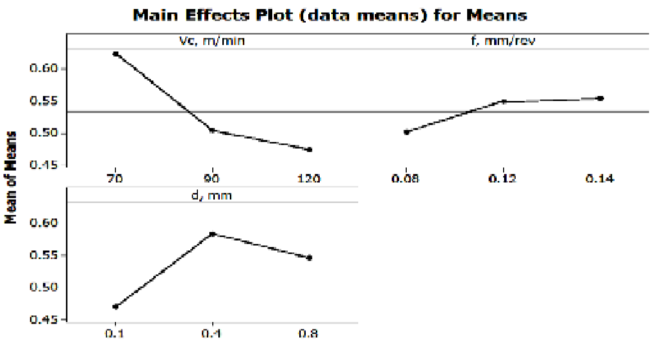


Figure 4.2 Main effect plot for uncoated inserts

4.4 PREDICTIONS BASED ON ANN

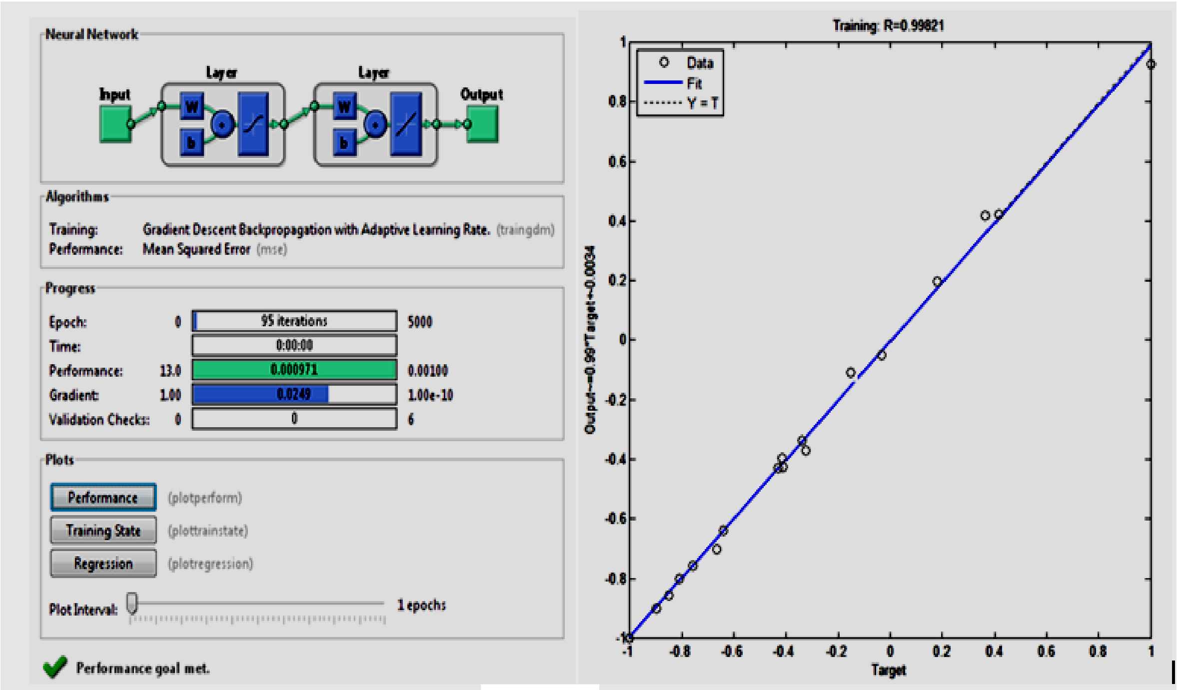
The ANN is an efficient quantitative tool to predict the MPCI.

Due to presence of non-linearity in turning process prediction of MPCI is done using conjugate gradient back propagation ANN [50]. ANN splits the data into training and testing sets and the studies were carried out by using MATLAB simulation environment. The network is trained with selected input parameters (Table 4.9) for seventy five percent of experimental data. For our ANN prediction, the input parameters used are the three main machining input parameters (cutting speed, feed rate, depth of cut), while the output dataset are MPCIs. Each pattern is formed with an input condition vector (Pi) and the corresponding target vector (Ti), which is shown in the matrix. Before training the network, the input-output dataset were normalized within the range of -1 to +1 using the MATLAB command 'premnmx'. The network architecture/ topology or features such as number of neurons and layers are very important factors that determine the functionality and generalization capability of the network .Training of an ANN plays a significant role in designing the direct ANN-based prediction.

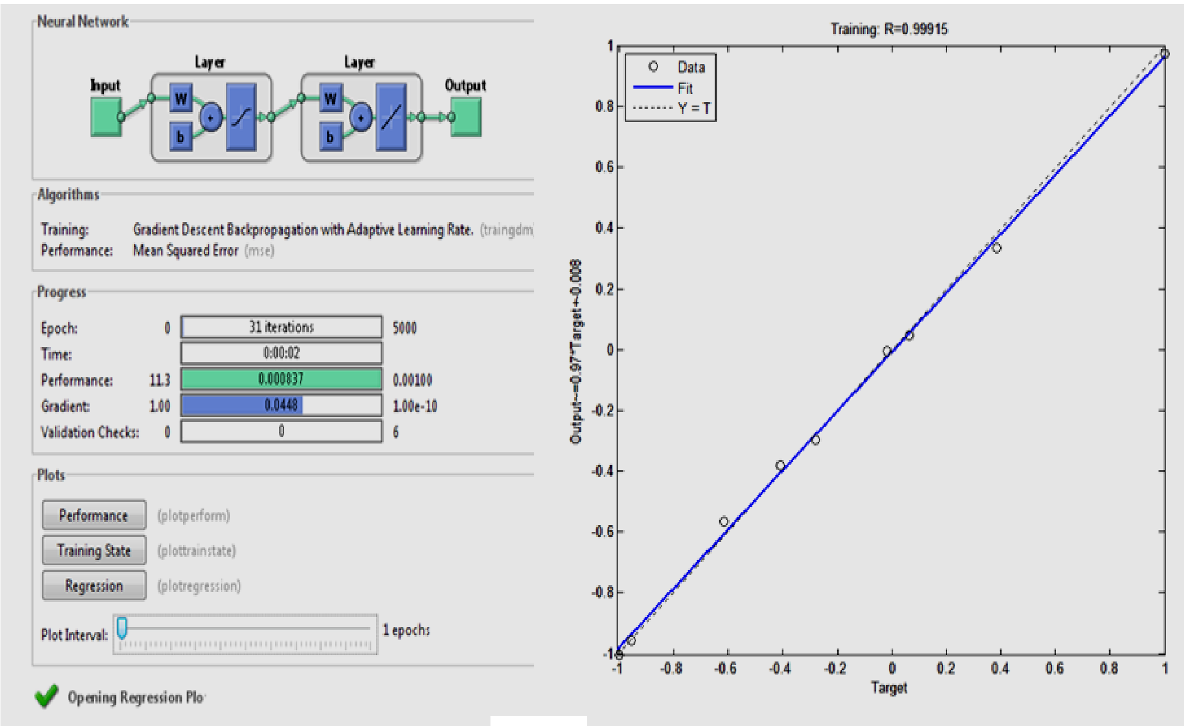
The comparison between the experimental result and the predicted result based on Taguchi and ANN of OA data is shown in Table 4.10.

$$P_i = \begin{bmatrix} Cutting\ velocity, V \\ Feed, f \\ Depth\ of\ cut, d \end{bmatrix} T_i = \begin{vmatrix} \text{MPCI} \end{vmatrix}$$

TABLE 4.9 Input parameters selected for training and testing	
Input parameters for training	Values
Error tolerance (goal)	0.00001
Show	50
Number of epochs	2,000
Number of neurons in the hidden layer (H)	5
Number of input layer neuron (I)	3
Number of output layer neuron (O)	1

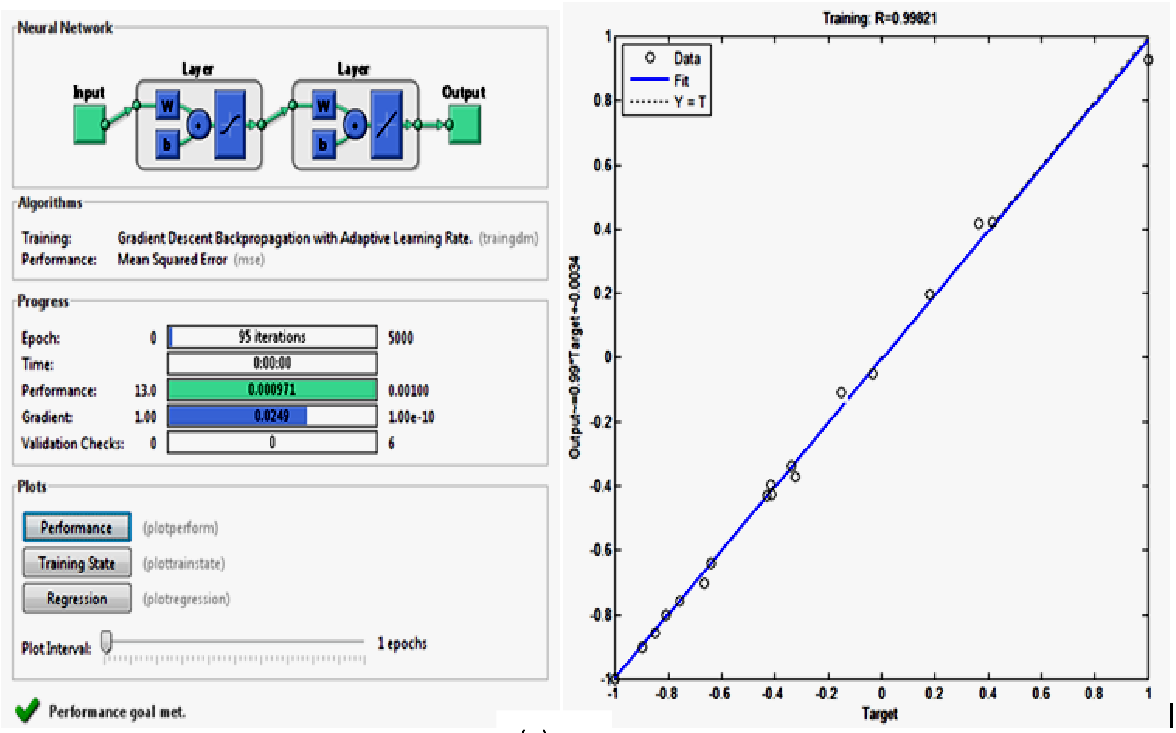


(a)

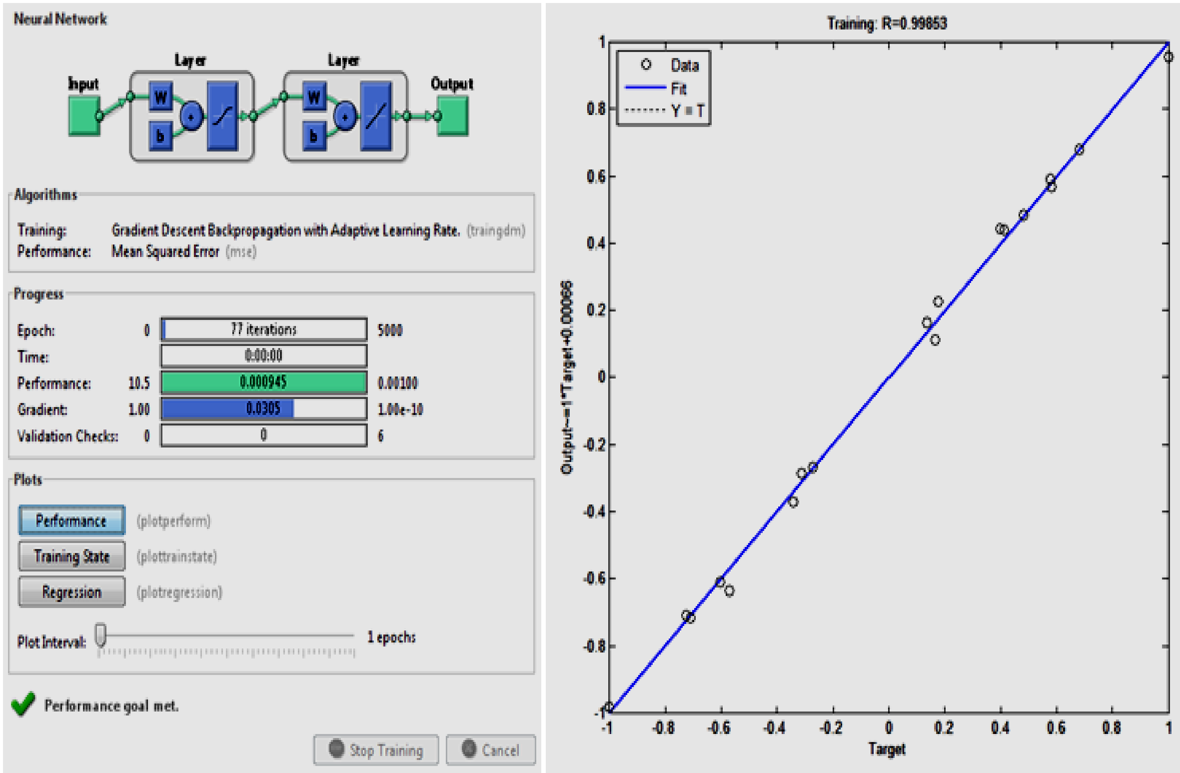


(b)

Figure 4.3 ANN model and correlation between the predicted values of the neural network model and the experimental data for prediction of MPCI using the training (a) testing (b) for coated inserts



(a)



(b)

Figure 4.4 ANN model and correlation between the predicted values of the neural network model and the experimental data for prediction of MPCI using the training (a) testing(b) for uncoated inserts

4.5 COMPARISON OF EXPERIMENTAL AND ANN RESULTS

TABLE 4.10
Comparison of Experimental result, Taguchi and ANN predicted results of OA data

Expt. No	Coated insert			Uncoated insert		
	Experimental MPCI	Predicted MPCI by ANN	Relative error	Experimental MPCI	Predicted MPCI by ANN	Relative error
1	0.3320	0.3314	0.0017	0.4785	0.4724	0.0128
2	0.5623	0.5589	0.0061	0.6185	0.5898	0.0464
3	0.7743	0.7681	0.0080	0.7937	0.6683	0.1580
4	0.7185	0.7311	-0.0175	0.6867	0.7303	-0.0635
5	0.8747	0.8563	0.0211	0.7943	0.764	0.0382
6	0.5260	0.5316	-0.0107	0.8207	0.8305	-0.0119
7	0.6206	0.6165	0.0065	0.7573	0.6963	0.0806
8	0.6732	0.6769	-0.0055	0.8864	0.8502	0.0409
9	0.5275	0.5239	0.0069	0.8366	0.7939	0.0511
10	0.3217	0.3205	0.0036	0.4730	0.4946	-0.0457
11	0.4558	0.4618	-0.0132	0.5392	0.6407	-0.1882
12	0.4086	0.4201	-0.0281	0.5492	0.5453	0.0072
13	0.4646	0.4562	0.0181	0.5723	0.4938	0.1372
14	0.5853	0.6020	-0.0285	0.7553	0.5988	0.2072
15	0.5490	0.5377	0.0205	0.7508	0.739	0.0158
16	0.4708	0.4712	-0.0008	0.6396	0.5731	0.1040
17	0.7315	0.7326	-0.0015	0.7916	0.7703	0.0269
18	0.5448	0.5461	-0.0024	0.8203	0.8225	-0.0026
19	0.4850	0.4810	0.0082	0.4860	0.5063	-0.0418
20	0.5437	0.5474	-0.0068	0.6938	0.6633	0.0440
21	0.6355	0.6238	0.0184	0.6639	0.6694	-0.0083
22	0.4077	0.4066	0.0028	0.6177	0.6066	0.0180
23	0.3825	0.3828	-0.0007	0.6153	0.5994	0.0259
24	0.4294	0.4313	-0.0043	0.6344	0.636	-0.0025
25	0.4193	0.4175	0.0042	0.6801	0.6641	0.0236
26	0.4421	0.4422	-0.0003	0.6753	0.6435	0.0471
27	0.5223	0.5230	-0.0013	0.8050	0.8097	-0.0059

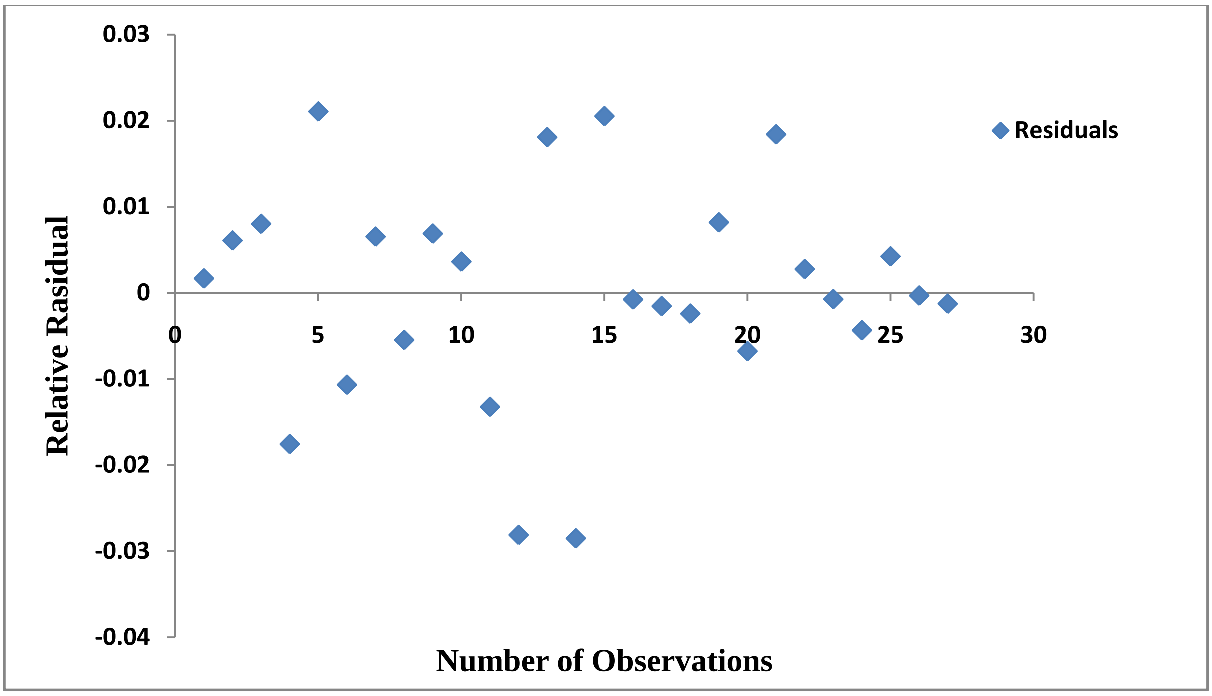


Figure 4.5 Relative error plot for coated insert

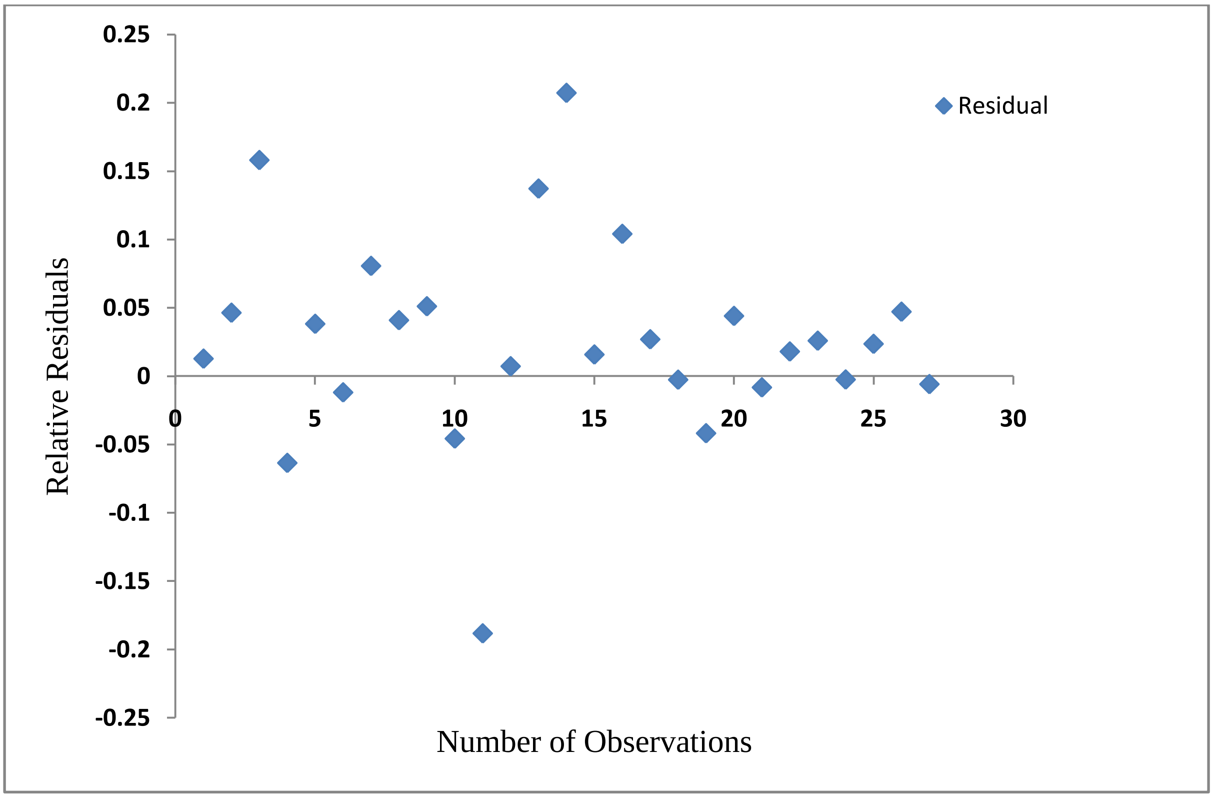


Figure 4.6 Relative error plot for uncoated insert

CHAPTER 5

CONCLUSIONS

CONCLUSIONS

1. Taguchi approach along with PCA and ANN is very simple and efficient way to find out the optimality condition with multiple responses and its predicted value.
2. An ANN model predicted the output response as a function of cutting parameters. The model has been proved to be successful in terms of agreement with experimental results as the relative errors are very less. From the relative error plots it is found that points are randomly and dispersly distributed and hence the data predicted are significantly fit to the model. The proposed model can be used in optimization of cutting process for efficient and economic production by forecasting the responses in turning operations.
3. Application of PCA has been recommended to eliminate response correlation by converting correlated responses into uncorrelated quality indices called principal components which have been as treated as independent response variables for optimization. The approach can be recommended for continuous quality improvement and off-line quality control of a process/product.
4. The optimal cutting parameters are found to be velocity of 70 m/min, feed rate of 0.14 mm/rev and depth of cut of 0.8 mm and velocity of 70 m/min, feed rate of 0.14 mm/rev and depth of cut of 0.4 mm for coated and uncoated inserts respectively for minimizing responses while turning.
5. Analysis of variance indicates that cutting Analysis of variance indicates that cutting velocity is the most influencing parameter for minimizing responses in both the tool conditions.
6. In case of coated carbide the surface roughness is 10-12%, flank wear 5-10% and cutting forces are 10-20% less as compared to uncoated carbides.

Scope for Future work

The modeling and analysis can be extended considering vibration of machine tool and tool chatter in future.

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